Critical Trigger Mechanism – a Modeling Paradigm for Cognitive Science Application

in the Design of Artificial Learning Systems

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ABSTRACT

In our present *short paper* we introduce a rather promising modeling paradigm for the design of artificial learning systems, incorporating *critical trigger mechanism (CTM)*. We contend that at various stages of the learning process, such trigger mechanism may be activated when certain 'critical' points in the learning curve are attained. Such points are marked by *fuzzification* of the learner's decision set. At all other 'non-critical' points where the decision set is crisp, this trigger mechanism lies dormant. We proceed to show that identification and subsequent incorporation of such trigger mechanisms will be of substantial help in modeling learning systems that closely emulate cognitive learning pattern of the human mind. This is not a complete work in any sense but just an indication of what is to come - a mere map of the long and challenging road ahead.

Key Words

Artificial Learning Systems, Fuzzy Logic, Cognitive Science, Directed and Non-directed Interventions

Introduction

The conditioned-reflex experiments of the Russian physiologist Ivan Pavlov and the American psychologist Edward Thorndike were central to the development of behaviorist model of learning. However, modern cognitive science favors a logical-computational model of learning over the rather mechanistic stimulus-response model of traditional behaviorism. But there need not exist as big a chasm between the approach of traditional behaviorism and that of modern cognitive psychology as is often made out to be. Gagne and Briggs (1974) have already attempted to combine behaviorist principles of learning with a cognitive theory of learning named Information-Processing. They believe that the design of intervention must be undertaken with suitable attention to the conditions under which learning occurs.

Information-Processing theory regards human learning as being analogous to a computer and its ability to store memory. Significant efforts have already been made to design artificial systems that emulate human learning and memory. In this regard, the ***Memory Extender (ME)*** personal filing system design is an illustrative example that immediately springs to mind. As humans we process information initially with our senses. This information is either processed into short-term memory or is lost. If this information is continually re-used it is processed into long-term memory. However, for this information processing there has to be some initial directed interventions ***(hard programming)*** followed by subsequent non-directed interventions ***(soft programming)***. At times, these two forms of intervention may become mutually inconsistent. It is especially to deal with such situations that we suggest the incorporation of *critical trigger mechanism (CTM)*, in order to make the system decide upon a definite course of action.

The Proposed Modeling Paradigm

Let us consider a case where an artificial learning system is being trained to emulate investor behavior. The fundamental operational rule which the system needs to learn is a simple IF statement – ***"Buy IF price is rising AND Sell IF price is falling"***. But simply learning this fundamental rule may not enable the system to realistically emulate the actual behavior of a human investor. The fundamental rule is nevertheless important – it is the initial hard programming bit consisting of a directed intervention. This is the easy part. But for a realistic simulation, the system must also learn to do some internal cognitive processing in accordance with one or more subsequent non-directed interventions – the soft programming bit.

If we are trying to design a system to emulate an individual investor's fund allocation behavior then we have to prima facie consider the subtle cognitive factors underlying such behavior over and above those dictated by hard economic reasoning. The boundary between the preference sets of an individual investor, for funds allocation between a risk-free asset and the risky market portfolio, tends to be rather fuzzy as the investor continually evaluates and shifts his or her position; unless it is a passive *buy-and-hold* kind of portfolio.

Thus, if the universe of discourse is $\mathbf{U = \{C, N, A\}}$ where C, N and A are three risk classes **"conservative"**, **"neutral"** and **"aggressive"** respectively, then the fuzzy subset of U given by $\mathbf{P = \{x_1/C, x_2/N, x_3/A\}}$ is the true preference set for our purposes. Here we have $\mathbf{0 \leq (x_1, x_2, x_3) \leq 1}$, all the symbols having their usual meanings. Although theoretically any of the $\mathbf{P(x_i)}$ values could be equal to unity, in reality it is far more likely that $\mathbf{P(x_i) < 1}$ **for** $\mathbf{i = 1, 2, 3}$ i.e. the fuzzy subset P is most likely to be ***subnormal***. Also, similarly, in most real-life cases it is expected that $\mathbf{P(x_i) > 0}$ **for** $\mathbf{i = 1, 2, 3}$ i.e. all the elements of P will be included in its support: **supp (P) = {C, N, A,} = U**.

The critical point of analysis is definitely the individual investor's preference ordering i.e. whether an investor is primarily conservative or primarily aggressive. It is understandable that a primarily conservative investor could behave aggressively at times and vice versa but in general, their behavior will be in line with their classification. So the classification often depends on the height of the fuzzy subset P: **height (P) = $\mathbf{Max_x P (x)}$**. So one would think that the risk-neutral class becomes largely superfluous, as investors in general will tend to get classified as either primarily conservative or primarily aggressive. However, as already said, in reality, the element N will also generally have a non-zero degree of membership in the fuzzy subset and hence cannot be dropped.

The fuzziness surrounding investor classification stems from the fuzziness in the preference relations regarding the allocation of funds between the risk-free and the risky assets in the optimal portfolio. It may be mathematically described as follows:

Let M be the set of allocation options open to the investor. Then, the fuzzy preference relation is a fuzzy subset of the **M x M** space identifiable by the following membership function:

$$\begin{aligned} \mu R (m_i, m_j) &= 1; \ m_i \text{ is definitely preferred to mj} \\ &c \in (0.5, 1); \ m_i \text{ is somewhat preferred to mj} \\ &0.5; \text{ point of perfect neutrality} \\ &d \in (0, 0.5); \ m_j \text{ is somewhat preferred to mi; and} \\ &0; \ m_j \text{ is definitely preferred to mi} \end{aligned}$$

The fuzzy preference relation is assumed to meet the necessary conditions of reciprocity and transitivity. Then a CTM would be a built-in function in conjunction with the above membership function, such that, when activated, it would instantaneously convert the fuzzy preference relation into a crisp preference relation.

As long as a subsequent soft programming is consistent with the initial hard programming, the decision set will be crisp: the universe of discourse and the crisp decision subsets being of the following form:

$$\begin{aligned} &D = \{d_1, d_2 \ldots d_i \ldots d_n\}; \\ &d = \{d_1, d_2 \ldots d_i \ldots d_k, (d_i \in D) \cap (d_i \notin d^c)\}, \\ &d^c = \{d_{k+1}, d_{k+2} \ldots d_{k+i} \ldots d_n, (d_{k+i} \in D) \cap (d_{k+i} \notin d)\}, \text{ such that } d \cap d^c = \phi \end{aligned}$$

However, at a point of conflict between the initial hard programming and a subsequent soft programming, the decision set will be fuzzified with an unchanged universe of discourse but fuzzy decision subsets of the following form:

$$\begin{aligned} &D = \{d_1, d_2 \ldots d_i \ldots d_n\}; \\ &d = \{p_1/d_1, p_2/d_2 \ldots p_i/d_i \ldots p_n/d_n, (d_i \in D), (0 \le p_i \le 1)\}, \\ &d^c = \{q_1/d_1, q_2/d_2 \ldots q_i/d_i \ldots q_n/d_n, (d_i \in D), (0 \le q_i \le 1)\}, \\ &\text{such that } d \cap d^c \neq \phi \end{aligned}$$

Therefore, any function having the potential to be a CTM must be having the following fundamental characteristics:

- **It should be activated if and only if the decision set is fuzzified at any stage in the learning process**
- **It should, when activated, convert a fuzzy decision set into a crisp decision set**
- **It should mark a critical point on the system learning curve by either advancing or setting back the learning process**

Suppose a novice investor goes on putting more and more of his or her funds in a particular asset just because it has been steadily outperforming the market index over the recent past. Then, suddenly one fine day the bubble bursts and our investor is left in the red with the greater part of his or her equity wiped out. How far will that investor be inclined to invest in a similar asset in the distant future when such type of assets are doing great once again? Economic reasoning (hard programming) will encourage the investor to go with the trend and once again start putting his or her funds on that asset. But the investor's cognitive process (soft programming) may not be in tune with the directed intervention of market economics. This would ***fuzzify*** the decision set for the investor. This is where a potential CTM could be activated which ultimately decides which way the investor would go by ***de-fuzzifying*** the decision set.

In case of our investor, if the CTM activation actually hinders learning then he or she will be inclined to leave that offending asset alone no matter how lucrative an investment opportunity seems. If on the other hand the CTM activation actually facilitates learning then the investor will go for that asset once again but adopt a more circumspect approach – having positively ***learned*** from his or her previous misadventure. However, in either case, the CTM has the effect of ***de-fuzzifying*** the investor's decision set.

The extent of potential impact of the CTM could also be effectively modeled as a fuzzy function characterized by the universe of discourse $\{C_S, C_M, C_W\}$ corresponding to **"strong"**, **"moderate"** or **"weak"** impact respectively, with the governing fuzzy subset $\{\theta_1/C_S, \theta_2/C_M, \theta_3/C_W\}$; $(0 \leq \theta_1, \theta_2, \theta_3 \leq 1)$. An artificial learning system would have an advantage in this regard as such a system could incorporate the different possible forms (at varying strengths of impact) of the CTM and perform a ***what-if*** analysis to see exactly how different the individual outcomes are in each case.

The Road Ahead

What we have here is some kind of a hypothesis regarding modeling of artificial learning systems that emulate the human learning process. As our next step we plan to identify a potential CTM in human learning behavior specifically in relation to investing. One prime candidate we feel could be the ***post-investment cognitive dissonance factor*** due to inconsistency in perceived and true worth of an investment, which can and often do critically affect an investor's learning behavior. Subsequently, we propose to incorporate this mechanism in a ***hybrid neuro-fuzzy system*** and emulate investor behavior under different market settings. If results are satisfactory then the approach could be extended to models covering other facets of human learning behavior. Finally we would need an ***effective integration strategy*** to bring the various models together in a unified whole. Once this integration is achieved over a fairly large area of human learning, we shall have moved one significant step forward in creating the ultimate of all artificial learning systems – a working model of the human mind.

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