Using Decision Trees to Model an Emotional Attention Mechanism

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Abstract: There are several approaches to emotions in AI, most of which are inspired by human emotional states and their arousal mechanisms. These approaches usually use high-level models of human emotions that are too complex to be directly applicable in simple artificial systems. It seems that a new approach to emotions, based on their functional role in information processing in mind, can help us to construct models of emotions that are both valid and simple. In this paper, we will try to present a model of emotions based on their role in controlling the attention. We will evaluate the performance of the model and show how it can be affected by some structural and environmental factors.

Keywords: Emotions, Attention, Artificial Intelligence

Introduction

There exist several emotion theories that have been applied to produce emotional artificial systems and researchers such as Elliott [1, 2], Dyer [3, 4], Pfeifer [5, 6, 7, 8] and Reilly [9, 10] have implement models of emotion management mechanisms in AI systems.

The emotion generation mechanism in human's mind presents several features that have key roles in information processing tasks like resource management, attention, learning and decision making. Modeling these features can help us not only to understand the concept of emotions but also to construct systems with a higher performance. For example, Harati Zadeh et. al [11] showed that a resource management approach to emotion could be applied in agents' decision-making system to improve its performance and generate a behavior that can be interpreted as emotional by human observers.

In this paper we will focus on the role of emotions in controlling the attention, and will try to model this feature of emotions for a system that has a single limited capacity input channel that can check one input at a time. Our goal is not to present a complete emotion enabled system or to construct a perfect attention mechanism for a complex intelligent system. But we will try to show how emotions could have an attention-controlling role in artificial intelligent systems and how a simple emotion driven attention system could be affected by some key parameters of the system and the environment in which it is applied.

A final note that seems to be necessary is that in this paper we will refer to the proposed models as "emotional" or "emotion-driven" ones. Our purpose is to emphasis that some aspects of those models are inspired from emotion system of human and it does not mean that we believe that they are complete models of emotions.

1. Attention and Decision Making

When someone enters some emotional state, he/she becomes more sensitive to some inputs, while ignoring the other ones that may be important in non-emotional states. For example someone who has been frightened strongly, possibly will temporarily forget the signals that say he/she is hungry.

New cognitive/computational theories of emotions, define emotional states as configuration of mental resources [12]. According to this definition, each emotional state, reconfigures the mental resources and helps the mind to change its behavior according to current situation. One of the possible effects of emotions could be the adjustment of the attention mechanism.

In AI domain, usually the researchers assume that the system receives all of *available* input values from its environment, based on which the system can define the current state and decide about the next action. However when the input channel of the agent has a limited band width, that is the agent must pay for checking each single input value, an attention guide system will improve it performance by saving the computation time and space.

One of the concepts in AI that supports a simple form of attention is the decision tree. A decision tree can be translated to a set of checking priorities over the possible inputs. Through these priorities, the decision making system in each step puts a single input in its attention window based on the values of inputs checked so far. Therefore, the attention mechanism follows some general strategy that is implicitly defined by the decision tree.

There are several algorithms to construct decision trees [13]. Some of these algorithms construct the tree after the learning phase, and they assume that the agent has already gathered a complete set of knowledge from its experiences in the environment [14]. There exist other algorithms that let the agent to construct the tree incrementally [15]. In addition, some heuristics have been proposed to construct the trees in situations that the agent's knowledge is incomplete or inaccurate [16]. However, from the view point of attention, all of these algorithms are more or less the same. To make our discussion more clear, here we will assume that the agent's knowledge, and the decision tree constructed based on it, is correct, complete and sufficient for making correct decisions.

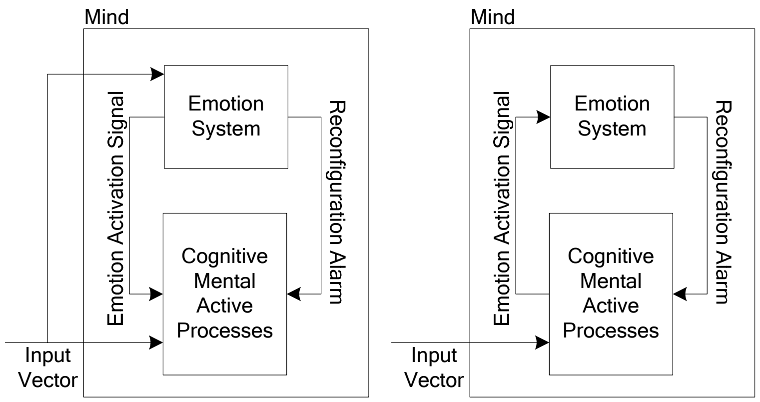

Figure 1: Explicit (left) and Implicit (right) emotion activation mechanisms

2. A Model for Emotional Attention

Amygdala is a part of the brain that is responsible for most of emotion-related mental jobs [17]. This part receives sensory inputs as well as signals from various other parts of brain and generates emotional signals to pass to other areas in the brain especially to those that have important roles in decision-making [18].

Therefore, an emotional state can be initiated if Amygdala recognizes some certain pattern in raw sensory inputs, or if it receives some emotion arousing processes information from other parts of the brain (figure 1).

The main difference between these two types of emotion arousal is that in the first one, the emotion-activation mechanism monitors the input signals subconsciously, and activates an emotional state at the same time that the emotion-arousing pattern appears in input channel, however, in the second mechanism, subconscious input monitoring is not performed and therefore, the emotion activation is delayed until the conscious cognitive mechanisms identify the situation as emotional. In this paper we will refer to the first approach as explicit emotion activation and to the second one as implicit emotion activation.

In both cases there must be some sort of alarm system that informs mind about the new active emotion according which the mind could be reconfigured to prepare for the new situation [19]. However, from the viewpoint of attention mechanism, this reconfiguration means deactivating the current attention strategy and activating a new one. Therefore, the general model of emotion driven attention system will be like the one depicted in figure 2.

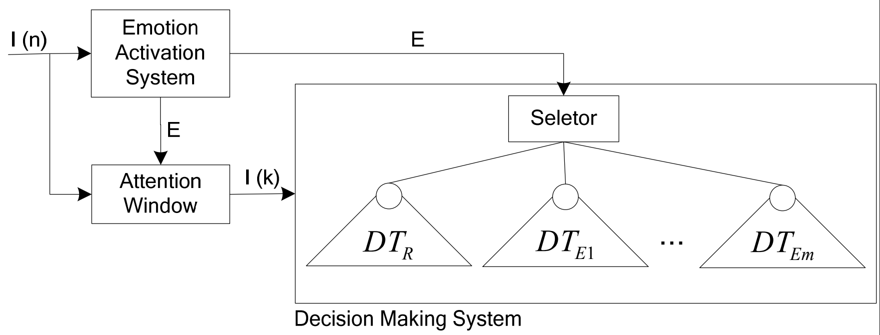

Figure 2: Emotion driven attention mechanism for a system using decision-trees

In this schema, “I” stands for input vector, “n” and “k” determine the number of inputs in the input vector and “k” is smaller than or equal to “n”. The Attention Window could be imagined as a filter or mask that passes useful input values and hide other ones from decision making system. The signal “E” going out from Emotion Activation System reconfigures attention window such that the input vector passing it is reduced to a subset of input values that are useful to making decision in current situation. The same signal goes to Decision Making System to inform it about current active emotion.

The agent uses decision trees for making decision so it must have a decision tree constructed based on each “k” values that it receives through the attention window. In other words the decision maker will have a set of decision trees of which, one is for non-emotional states and the others are for emotional states.

As shown in this schema, the selector subsystem uses the current active emotion signal “E” to select the suitable decision tree that is the suitable attention-shifting sequence, for current state. DT_R is the decision tree for non-emotional state and DT_{E1} to DT_{Em} are decision trees for emotional states constructed according to the input values that the decision making system receives in those states.

In the next subsections we will explain how the explicit and implicit emotion activation mechanisms can be embedded in presented general model for attention. We will refer to the attention mechanism based on explicit emotion activation as "explicit emotional attention system" and the one based on the implicit emotion activation as "implicit emotional attention system".

2.1. Explicit emotional attention system

This version of attention system is based on subconscious input monitoring that does not use sophisticated cognitive mechanisms. Therefore we will try to keep the mechanism of emotion activation as simple as possible. To do so, we decided to construct the emotion interrupt system such that each emotion is sensitive to only one input variable and the corresponding emotion signal is triggered when that input variable takes a certain value. In addition, we have assumed that the maximum number of emotions is known in advance.

Assuming that the system already has the required rule base for making the best decisions, the algorithm presented in figure 3 will use the agent's knowledge to construct its emotion set. In this algorithm, all the inputs have been assumed to take values in a discrete domain. This algorithm checks all the situations that may arise by setting one of the inputs to a specific value in its domain. For each (input, value) pair there is a set of rules in the rule base that can be applied at least in one of those situations. Based on these rules, the agent can construct a decision tree that is smaller than the main decision tree constructed based on the whole rule base, but is valid only when "input = value". Therefore, if the agent be somehow informed that this condition is met, for example through the emotion system, it will be able to check fewer inputs by using it instead of the main decision tree. However, since the capacity of interrupt system is limited, the agent must assign interrupt signals to the situations that their corresponding decision trees cause more reduction in input checking.

An important aspect of this algorithm is that it excludes the part of rule base that matches with activation criteria for emotion defined so far before going to the next turn to find the next emotion (line 7). In the emotion system, the emotions extracted first will have a higher priority than those ones that have been extracted later.

1- Construct the Main Decision Tree (MDT) based on complete knowledge base.

2- Compute the average number of input checks for MDT.

3- For each input "i"

   a. For each possible value "v" for "I":

      i. If there is no rule in knowledge base in which i = v, ignore v.

      ii. Construct the decision tree $DT_{i=v}$ based on those rules in which i = v

      iii. Compute the Average number of Input checks "AIC" for $DT_{i=v}$

      iv. Compute the Average number of Input Checks "MAIC" in MDT, for the states in which i = v.

      v. Define the average check reduction ACR as "MAIC – AIC".

4- If no (i , v) causes a check reduction bigger than zero terminate the process.

5- Find the input "I" and value "V" such that $DT_{I=V}$ presents the maximum average check reduction.

6- Add emotion $E_{I=V}$ with the condition I = V to the emotion interrupt system.

7- Exclude the rules in which I=V from the knowledge base.

8- If the emotion system has space to add another emotion, go to step 1.

Figure 3. The algorithm for defining emotion interrupts

2.2. Implicit emotional attention system

In many applications, like most software intelligent systems, the agent is not always able to have an interrupt mechanism and it must pay for each single input that is checked. To evaluate the performance of an emotion driven attention system in such environments we replaced the explicit emotional attention mechanism with the implicit one that is initiated inside the agent's decision making system (figure 4).

As presented in figure 5, in this model, the agent assigns emotion labels to certain input values. When the agent faces one of these input values during its non-emotional decision-making, it deactivates the current input priorities, and activates the emotion assigned to that input value. The active emotion proposes its own policy for agent's attention system, and the agent uses that policy as long as the emotion proposing it is active. When the agent returns to non-emotional state, the non-emotional attention policy will be activated again.

The algorithm shown in figure 5 shows the emotion extraction mechanism for this version of the attention system. As it is clear, this algorithm does not exclude the part of knowledge matching with emotions defined so far from the knowledge base. Therefore, the MDT does not change during the emotion definition process.

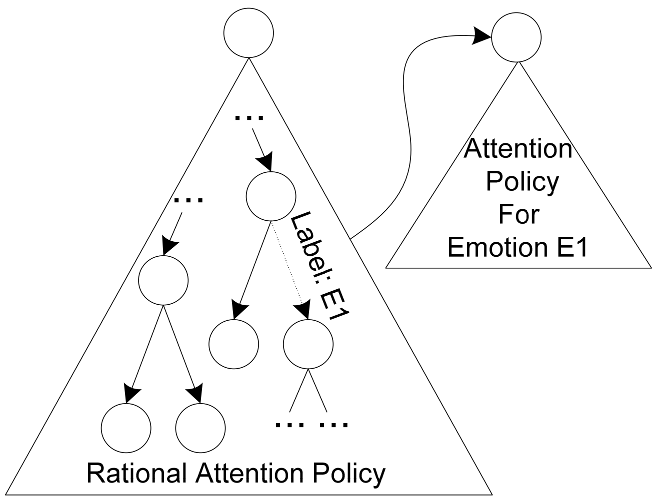

Figure 4. Emotion activation labels in implicit emotion driven attention mechanism

1- Construct the Main Decision Tree (MDT) based on complete knowledge base.
2- Compute the average number of input checks for MDT.
3- For each input “i”
    a. For each possible value “v” for “I”:
        i. If there is no rule in knowledge base in which i = v, ignore v.
           Construct the decision tree $DT_{i=v}$ based on those rules in which i = v
        ii. Compute the Average number of Input Checks “AIC” for $DT_{i=v}$
        iii. Compute the Average number of Input Checks “MAIC” in MDT, for the states in which i = v.
        iv. Define the average check reduction ACR as “MAIC – AIC”.
4- Find the input “I” and value “V” such that “$DT_{I=V}$” presents the maximum average check reduction bigger than zero and no emotion with condition I = V has already been defined.
5- If no such “I” and “V” found terminate the process.
6- Add emotion $E_{I=V}$ with the condition I = V to the emotion system.
7- Add the label “$E_{I=V}$” to all of arcs in MDT that assign value “V” to input “I”.
8- Go to step 3.

Figure5 . The algorithm for defining emotions for implicit emotional attention system

3. Implementation and Results

To implement the proposed model we used a model of an agent living in an environment called Logic World. In Logic World, there are a set of Boolean variables and values of these variables define the current state of the environment. Each state remains active for a predefined period and then the values of variables change randomly. The correct action that the agent must do in each state is defined by a function called behavioral function. We have assumed that the agent has already learnt the behavioral function through previous experiences during its life. Its knowledge base contains a set of rules assigning an action to each state; however, the agent is not aware of the current state of the environment before checking the inputs it receives. In each experience, if the correct action is selected, the agent receives a positive reward value and if not, it is punished by a negative penalty.

The agent uses emotion extraction process, to build an explicit or implicit emotional attention control mechanism. We have performed a series of tests to examine the effect of these emotion driven mechanisms on the average reward that the agent receives in long term.

The emotion arousal process and its effect on the system’s performance could be affected by several parameters, among which we focus on some of the most important ones, for which the results are presented. In following test, the average reward is computed for 10 million decisions. The agent receives “+1” reward for a correct action and “-1” penalty for a wrong one. Emotional agent has five emotions with inertia equal to 5 cycles, 10 possible actions and receives an input vector with 15 inputs. We will mention it if a test has different values for these parameters.

- **Complexity of the environment and Diversity of the actions space**

In Logic World the complexity of the environment is solely defined by the number of inputs that have a role in behavior function. In simple environments the correct action could be deduced from a smaller set of inputs while in more complex environments agent must check several inputs before it can decide. The plot shown in figure 6 (left) presents the average reward that the agent receives for different sizes of input vector.

Another important parameter in an agent's performance is the number of actions it can choose. For an agent with a small set of actions, the behavior is more reactive, while for an agent with a rich set of actions, there are more choices in each cycle, and therefore more deliberation is required to make a correct decision. The graphs shown in figure 6 (right) presents the average reward received by the agent using each of emotional attention control systems with different number of possible actions to choose.

The results show that the average reward decreases as the size of input vector increases. It says that the more complex is the agent environment, the richer set of emotions is required for keeping the agent's performance at a constant level. There is no important difference between the two trajectories, except that the average reward received by the agent using explicit emotional attention system is higher than that of the agent using the

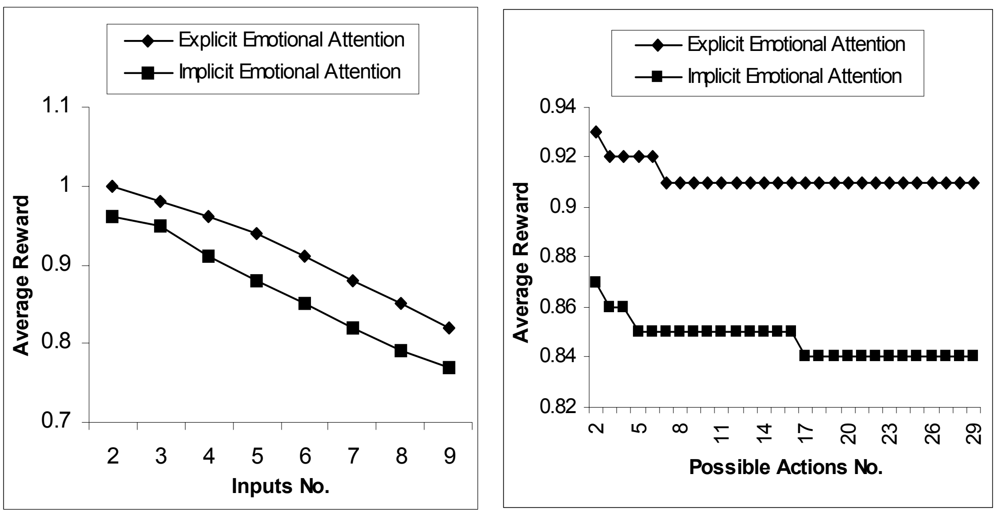

Figure 6. Average received reward vs. size of input vector (left) and number of possible actions (right)

other one. This is an expectable result, because an interrupt system like the one used in explicit emotional system does not waste the agent's time to activate the suitable emotion.

Also it can be seen that the explicit emotional attention mechanism is less sensitive to the number of actions compared with the implicit one. One explanation for this could be that the size of the rational decision tree that increases if we increase the number of possible actions. Therefore, the average number of inputs that the agent checks before it realizes that some emotional tree must be activated grows. This reduces the average reward that the agent with the implicit emotional attention system receives. The explicit emotional attention mechanism does not face this problem because the emotional situation is recognized directly and is not dependent to the size of the rational decision tree.

Another important result of this experiment is that both attention systems are more sensitive to the size of input vector compared to the number of possible actions. The performance of the agent remains constant if the number of possible actions stays in a certain domain, while it is decreased by each single input added to the input vector.

- **The number of emotions that the system supports and the effect of emotions' inertia**

Figure 7 shows the effect of increasing the number of emotions supported by the system on its performance. There are two sets of results for each system, one for emotions with constant predefined inertia and on for emotions with the perfect inertia. An emotion has a perfect inertia if it is active only if the current environmental state recommends it.

The results show that in explicit emotional system, the maximum number of emotions is smaller than that of the implicit emotional system. It is because the size of the non-emotional decision tree is reduced by adding each emotion to the explicit emotional system. Therefore, after constructing certain number of emotional interrupts, the non-emotional decision tree becomes so small that no new emotion can reduce its size, and the emotion extraction process stops.

Another important result of this test is that for the explicit emotional system the performance is the same for perfect and constant inertia. However for the implicit emotional system, the performance increases by new emotions with perfect inertia being added to the system, while adding emotions with constant inertia has a degrading effect on the average received reward. One can conclude from these results that the inertia assigned to each emotion has a very important role in system average performance. A wrong inertia for an emotion can cause the agent to stay in an emotional state while the environmental state has changed and does not recommend the active emotion anymore. This could be a very challenging problem if we want a system to assign the best inertia to its emotional states.

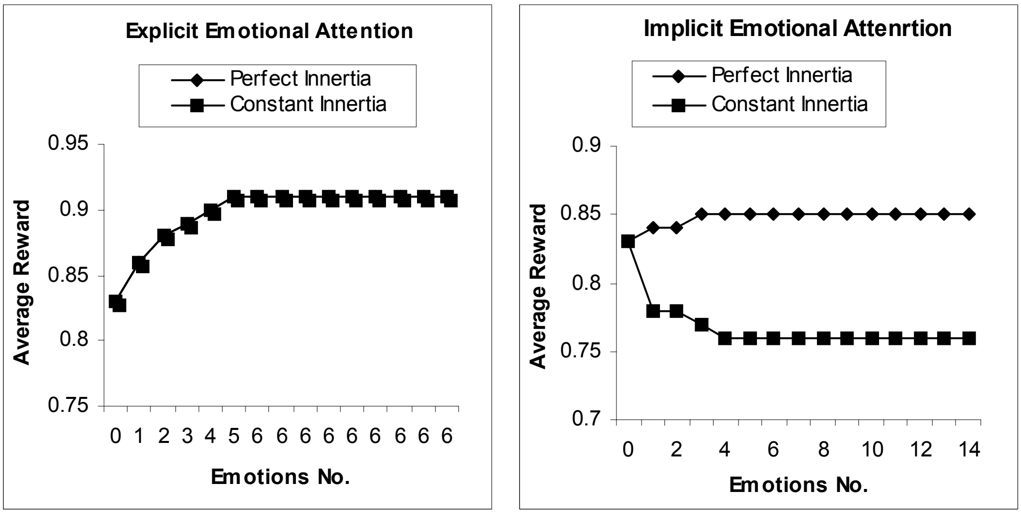

Figure 7. Average received reward vs. maximum number of definable emotions

4. Conclusion

In this paper, we tried to present two simple models of emotion-guided attention system. We evaluated the effect of some parameters that seem to be important in performance of such systems. The results of this experiment could be summarized as follows:

- An emotion driven attention mechanism, if implemented explicitly as an interrupt system, can improve the performance of the system. Explicit interrupt based emotional state are more beneficial without inertia.
- An implicit emotional attention mechanism can potentially increase the performance of the system given that the inertia values assigned to emotions are adjusted precisely. If inertia values are not picked accurately, the resulting emotion-enabled system may not be helpful and can lead to a performance lower than that of the emotion-less system. It is important to note that adjusting the emotions' inertia could be a difficult problem, because it has a strong relation with the definition of the emotional states and assignment of the environmental states to emotional states. Therefore these problems should be solved together.
- An emotion subsystem can improve the decision making at least in two ways:
    - o By reducing the amount of processing that the agent performs non-emotional situations.
    - o By providing a cheaper way to decide in emotional states.

Therefore, the goal of constructing each emotion determines the method using which one must construct it. In other word, the emotion definition is a context dependent task.

- Both the diversity of state space and the agent's action space have an important role in the performance of the presented emotion driven attention system, however, the first one affects the system more seriously.
- The performance of emotion activation mechanism is an important factor in emotion-enabled systems. An inefficient mechanism for recognizing the suitable emotion for current state can reduce the performance of whole system seriously. However, there is a trade of between allocating low extra resources for emotion subsystem and the performance that one can expect from it. Assigning some inertia to the emotions can help us to reduce the amount of processing that should be dedicated to the emotion activation mechanism.

In this paper we assumed that the required knowledge for building the emotional attention system has already been gathered by the agent and the emotion extraction process is performed on this knowledge. However finding incremental algorithms for generating emotion management mechanisms during agent's learning phase could be beneficial.

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