Application of Intelligent Reinforcement Theory for Efficient Affective Computing on Cloud

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Abstract – In this paper we have presented arobust machine learning technique whose aim is to efficiently analyze human emotions using affective computing technologies. The strategy is to deploy this technique in a cloud so that the load on user interface is minimized. We formulated this task of efficiently analyzing emotions as a multi armed bandit problem which if solved to maximize the rewards increases the efficiency of our technique. This paper paves the way for applying intelligent learning algorithms to solve affective computing challenges in future.

Index Terms – Reinforcement learning, Affective computing, multi armed bandit, Emotional analysis.

1. INTRODUCTION

Intelligent reinforcement learning is concept of machine learning where action of software agents determines the amount of reward obtained.In this paper, we propose strategies which maximize the notion of cumulative reward. Reinforcement learning is generally used in disciplines like multi agent systems, operations research, game theory, control theory. In computational field, reinforcement theory illustrates the stability of a state, which is bounded by rationality.

We derived our intelligent reinforcement learning model including below components:

1.An environment E and agent states S

2. A suit of action A_i for each action A_j

3.A set of state transitions denoted by $T_s = \{T_1, T_2, T_3, \ldots, T_n\}$

4.Reward associated after each state transition, $R= \{R_1, R_2, R_3, \ldots, R_n\}$

5.Rules that bind the agent's observation

In affective computing, precision of emotional analysis is an important measure which enhances the quality of the affective computing technology. It also depends on the quality of the collected data. The more the data, the higher will be the accuracy of emotional analysis. But, as the wearable technology has constraints in data collection and data storage .it arises a bottle neck. In order to reduce the bottle neck, we propose the intelligent reinforcement learning theory. Our learning theory involve the concept of modeling the maximization of reward for each agent's action as multi-armed Bandit problem. The multi-armed bandit problem is an optimization problem whose solution reduces remarkable outcome which are difficult to beat.

2. PROPOSED TECHNIQUE

The architecture of the proposed system is as follows:

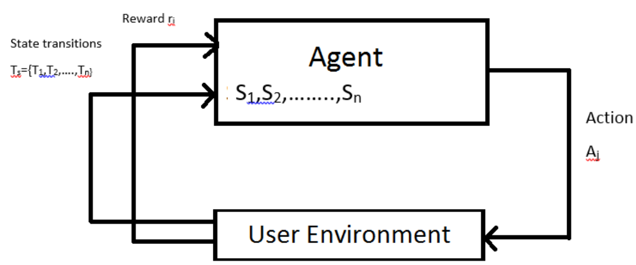

Fig.1.Proposed Architecture

The agent which undergoes reinforcement learning is placed in cloud. This agent acts on user environment where a series of state transitions trigger rewards for the agent. An optimal policy has to be constructed by the agent for which rewards are maximized. The agent learns from experiences as it explores the range of possible states.it updates the reward value in the cloud as the policy gets new information. For instance, if someone is performing emotional analysis then the agent may store emotions like person is happy, angry, sad, excited, etc. We can use any type of wearable technology to sense the data related to a specific emotion say extreme happiness has highest value. we represent this value by H. Similarly, extreme sadness will have L value. The reward will be high if agent learns to calculate difference between H & L which is a normal state. So, if H-L value is large, it means emotion is nearing H & vice-versa. Every state transition changes the value of H-L thus changing the reward value also. A Graphical representation is presented below:

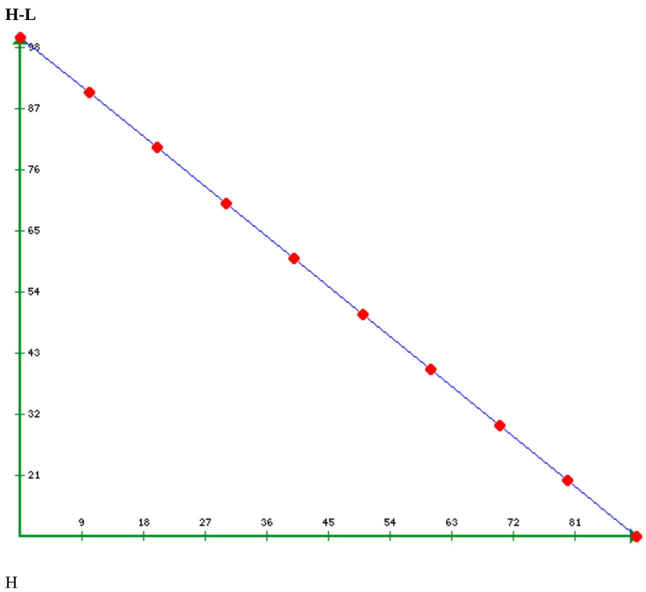

Fig.2.Graph between H versus H-L

On x axis we have happiness values and deviation from this values corresponds to the y axis. Finally, we can proceed to a generalization of our principle involved. The table below shows the reward/punishment incurred by agent for corresponding output after comparison of emotional values:

Comparisons of Emotional Values	**Reward/Punishment incurred**
Emvalue< Normal Value	Fear
Emvalue> Normal Value	Hope
action < Normal Value&Emvalue>action	Anger
act ion< Normal Value&Emvalue<action	Sadness
Emvalue2< Normal Value&Emvalue2> Emvalue2	Relief
Emvalue2> Normal Value&Emvalue1< Emvalue2	Disappointment
action > Normal Value&Emvalue2<action	Surprise
action > Normal Value	Joy

Table 1. Comparison between emotional values and corresponding Reward, punishment incurred

In the above table Normal Value refers to the average value of the emotion and Emvalue, Emvalue2 represents the values of emotions of the user which are input to the agent in cloud. Action indicates the deviation occurred in output after comparison is performed.

It can be easily predicted that after experiencing negative affect such as sadness, anger, and fear, humans prefer safer and higher rewards options. Sad individuals are motivated by an implicit goal of reward acquisition. Angry people tend to process heuristically, not thinking much about alternate solutions. Happy individuals are more likely to optimize or sacrifice in their decision making, rather than maximizing to achieve the best outcome.

3. CONCLUSION

We proposed an intelligent learning mechanism in this paper to deploy in a cloud with uses affective computing for emotional analysis. Emotional analysis is performed by our technique developed which is stable and it performs reward based actions only. When this reward based approach is repeated many times then a refined approach is the outcome. We obtain the reward based states by formulating the problem as multi armed bandit problem and solving it. In futurewe intend to extend the strategy to image processing and speech recognition domains.

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