

Implementation of Perception Classification based on BDI Model using Bayesian Classifier

Vishwanath Y¹ Murali T S² Dr M.V Vijayakumar³

¹Research Scholar, Dept. of Computer Science & Engineering, Jain University and Faculty, Dept. of Information Science & Engineering, New Horizon College of Engineering, Bangalore, India

²Freelance Software Developer, www.madrasi.asia, India

³Dept. of Computer Science & Engineering, Dr Ambedkar Institute of Technology, Bangalore, India

Abstract— Perception is an important aspect of cognition process. All the perceived data may not be essential for cognition process therefore we can classify the perceived data as essential and quintessential. We can save the essential in working memory and the quintessential in long term memory. Thereby enhancing the performance of the cognition process as only relevant information is available. The classification is done based on BDI (belief, desire and intention) model using naïve bayes classifier. The same has been implemented using SWI prolog and successfully classifying perceived data as effective and trivial perception based on BDI model using naïve bayes by first estimating the prior probability for effective and trivial perception and then likelihood probability.

Keywords— Perception, Cognitive Architecture, BDI Model, Naïve Bayes Classifier

I. INTRODUCTION

Perception is the interpretation of sensation that is conceived through senses. It refers to understanding of sensory information. Perception creates awareness about the environment through our senses. The way we perceive our environment is what makes us different from other animals and different from each other. Perception is a significant process in cognition [1]. Cognition is a mental process of acquiring, storing, representing, learning and inferring information. Cognition process is directly concerned with the functionalities of the brain and it is very dynamic [2]. The cognition process is considered to be in different states known as cognitive states. The human cognitive states are broadly classified into information acquisition, memory related, thought, motor action, emotion and others [3].

Cognitive architectures also called artificial mind models are defined as the design and organization of mind with ability to integrate all cognitive processes. A number of cognitive architectures have evolved over the period which are common in goal, but are different in concepts and methodologies. Some of the significant cognitive architectures are ACT-R (Adaptive control of thought-rational), SOAR (State Operator And Result), EM-ONE (Emotion Machine), SMCA (Society of Mind Cognitive Architecture) [4]. Most of these architectures are designed

with short term and long term memory [5]. The symbolic representation may be different with different architectures.

II. BACKGROUND

Perception is an important aspect of human life both in conscious states and subconscious states. The perception depends on the sensory neurons which are very noisy and unstable.

Perception is an important aspect of human life both in conscious states and subconscious states. The perception depends on the sensory neurons which are very noisy and unstable.

A small group of these neurons work together to form a stable perceptual representation [6]. This suggests that the perception information received may be classified. That is not all perceptual information received will be productive in cognition process. This ineffective class of perception we call it as trivial perception.

An unmanned vehicle is on mission to find water source on an undiscovered planet. The possible areas where the water may be available should have solar winds, comets, giant molecular clouds. The unmanned vehicle looks for these three parameters on the planet to detect water source. There are many other objects on the planet like craters, mare (seas), mountain or mountain ranges, rays, rills, breccias, rocks, etc. When the vehicle starts looking for water source the cognition process will consider only perception related to water and it becomes effective and on the other hand whatever other objects it perceives they become trivial perception.

III. PROBLEM STATEMENT

The perception is an important aspect of cognition [5]. In the cognition, the sensory information perceived through sensory devices will store in short-term memory (working memory). The stored information contains relevant and irrelevant data to the cognition process, which consumes the working memory and reduces the process. To overcome this issue, we classify the perception into effective and trivial. Thus, the effective perception will be stored in short-term memory and the trivial perception in long-term memory. The core issue is how to classify perception, so that there can be clear distinction between effective and trivial perception.

IV. CLASSIFICATION APPROACH

We find a number of factors that can be part of cognition and which influences the perception process.

We can also find that perceived information can be effective or ineffective information.

At this point we would like to classify perception as of two types 1) Effective 2) Trivial Perception can be represented as

$$\text{Perception} = \text{Effective perception} + \text{Trivial perception}$$

Effective perception can be represented as

$$\text{Effective perception} = \text{Perception} + \text{Attention}$$

Trivial perception can be represented as

$$\text{Trivial Perception} = \text{Perception} + \text{No Attention}$$

The classification can be enhanced by using deliberative (BDI) model. BDI (belief, desire and intention) are the mental components present in rational agent architectures [7].

Belief, desire and intention reflect motivation and learning. The BDI model intentions are adopted plans or strategies for achieving desires. Belief is the judgment along with desire and intention to reason.

The perception process in our proposal is shown in Fig.1 .The perceived sensory information is received and based on the factors belief, desire and intention the perceived information can be classified as effective and trivial perception.

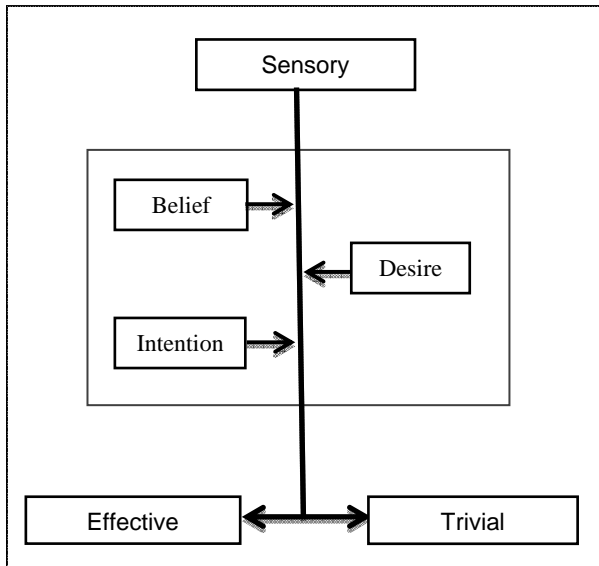


Fig. 1 Classification of perception

V. SIGNIFICANCE OF TRIVIAL PERCEPTION

Trivial perception is a very significant in two aspects 1. Reduces load on working memory, 2. Trivial perception at times transforms into effective and demonstrates intelligence. Elaborating on the second aspect consider the same scenario of searching for water source in an

undiscovered planet. Initially water source is effective perception and rest all becomes trivial. At later point of time after finding water source next if we are looking for some living organism in the same planet then instead of starting perception newly we can search the trivial perception that has accumulated in long term memory during search of water source. There is a possibility that living organism might have been perceived as trivial while water source was effective perception since living organisms are found near water source. This transformation of trivial to effective demonstrates intelligence. Human beings with this ability are considered to be intelligent. This skill is essential in managerial tasks, crime investigations, weather forecasts etc.

VI. MATHEMATICAL APPROACH

A. Naive Bayes Classifier:

The Naive Bayes Classifier is a simple probabilistic classifier technique that is based on the Bayesian theorem [8]. Though it is simple, Naive Bayes can often perform better than sophisticated classification methods. Naive Bayes classifier assumes that the presence (absence) of a feature in a class is unrelated to presence (absence) of another feature. Another advantage is small amount of training data is sufficient for classification.

Consider Fig. 2 and let Apple represents effective perception and Leaf represent trivial perception. Our task is to classify new cases as they arrive, and decide to which class label they belong Apple(effective) or Leaf(trivial), based on the currently existing objects.

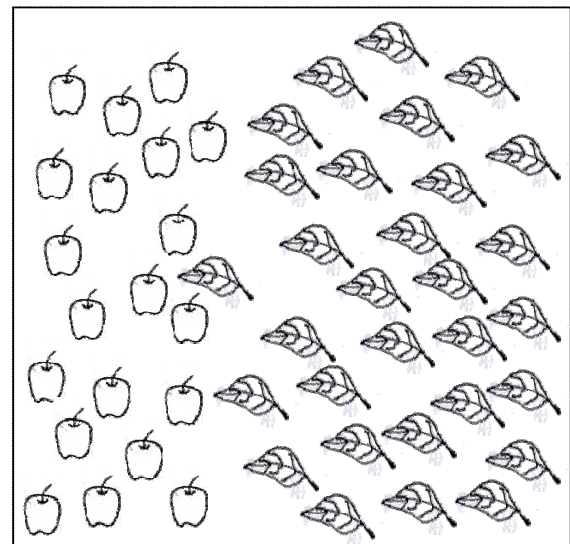


Fig. 3 Two types of objects Leaf and Apple

Since there are twice as many Leaf objects as Apple, it is reasonable to believe that a new case (which hasn't been observed yet) is twice as likely to have membership Leaf rather than Apple. In the Bayesian analysis, this belief is known as the prior probability. Prior probabilities are based on previous experience, in this case the percentage of Leaf

and Apple objects, are often used to predict outcomes before they actually happen.

Thus, it can be written as:

$$\text{Prior probability for Leaf } \propto \frac{\text{Number of Leaf objects}}{\text{Total number of objects}}$$

$$\text{Prior probability for Apple } \propto \frac{\text{Number of Apple objects}}{\text{Total number of objects}}$$

Since there is a total of 50 objects, 30 of which are Leaf and 20 Apple, our prior probabilities for class membership are:

$$\text{Prior probability for Leaf } \propto \frac{30}{50}$$

$$\text{Prior probability for Apple } \propto \frac{20}{50}$$

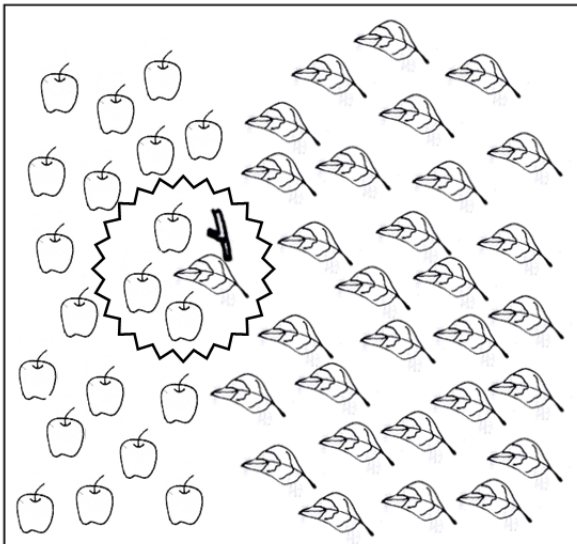


Fig. 4 Five objects encircled

Since we now have our prior probability, we are ready to classify a new object (A). Since the objects are well clustered, it is reasonable to assume that the more Leaf (or Apple) objects in the vicinity of X, the more likely that the new cases belong to that particular object. To measure this likelihood, we draw a 24-point star around X which encompasses a number (to be chosen a priori) of points irrespective of their class labels. Then we calculate the number of points in the Leaf belonging to each class label. From this we calculate the likelihood:

$$\text{Likelihood of X given leaf } \propto \frac{\text{Number of leaves in the vicinity of X}}{\text{Total number of Leaf cases}}$$

$$\text{Likelihood of X given Apple } \propto \frac{\text{Number of Apple in the vicinity of X}}{\text{Total number of Apple cases}}$$

From the illustration above, it is clear that Likelihood of X given leaves is smaller than Likelihood of X given Apple,

since the circle encompasses 1 Leaf object and 3 Apples. Thus:

$$\text{Probability of X given Leaf } \propto \frac{1}{30}$$

$$\text{Probability of X given Apple } \propto \frac{3}{20}$$

Although the prior probabilities indicate that X may belong to leaves (given that there are twice as many leaves compared to Apple) the likelihood indicates otherwise; that the class membership of X is Apple (given that there are more Apple objects in the vicinity of X than leaves). In the Bayesian analysis, the final classification is produced by combining both sources of information, i.e., the prior and the likelihood, to form a posterior probability using the so-called Bayes' rule.

$$\begin{aligned} &\text{Posterior probability of X being Leaf } \propto \\ &\text{Prior probability of Leaf } \times \text{Likelihood of X given Leaf} \\ &= 30/50 \times 1/30 = 1/50 \end{aligned}$$

$$\begin{aligned} &\text{Posterior probability of X being Apple } \propto \\ &\text{Prior probability of Apple } \times \text{Likelihood of X given Apple} \\ &= 20/50 \times 3/20 = 3/50 \end{aligned}$$

Finally, we classify X as Apple since its class membership achieves the largest posterior probability.

B. Algorithm

The classification of perception into trivial and effective is implemented based on BDI model using naïve bayes classifier. The flow chart in Fig. 5 depicts the classification process.

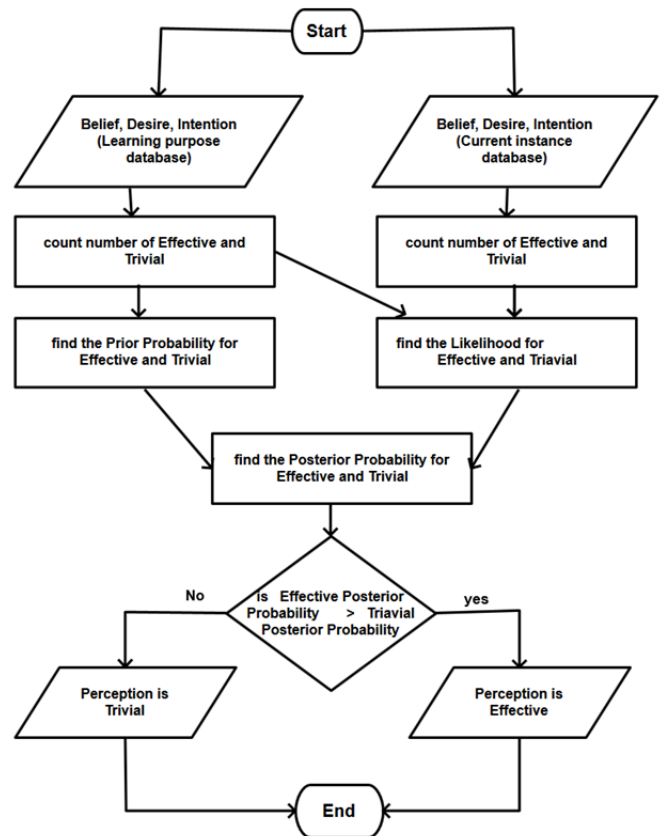


Fig. 5 Flow chart of perception classification

In naïve bayes classifier we compute prior probability for effective and trivial using the BDI data already in the database we call it as learning purpose database. Having computed prior probability next we classify current instance of BDI and find the likelihood for effective and trivial. By using prior probability and likelihood, we calculated the posterior probability. Then we compared the both effective and trivial posterior probability, the greater valued will be the classified perception.

C. Implementation

This concept is implemented by developing a simulation environment in the SWI-Prolog environment, with XPCE (a platform independent GUI toolkit for SWI-Prolog). Using XPCE tool, we created windows called user window and input window. The input window consist of input, perception and quit command buttons. By clicking on input button it opens the input window as shown in Fig. 7 And the user can input BDI values. The user can perform perception classification by clicking on perception command performs the operations of applying the Bayesian classifier theorem on the databases, process the operations on it and stores the detailed output into the output file as shown in Fig. 9 . The quit command button performs the action to quit the menu window.

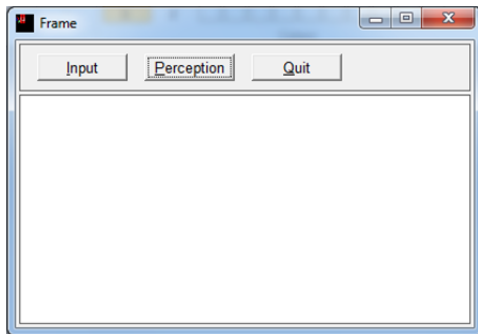


Fig. 6 User window

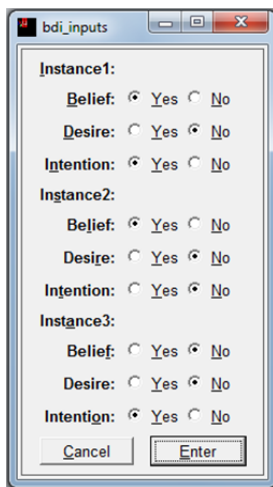


Fig. 7 User input window

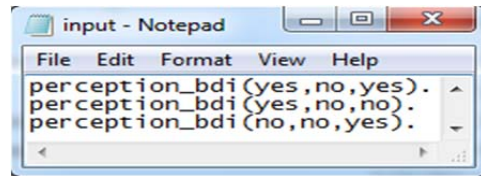


Fig. 8 Current instance input stored file

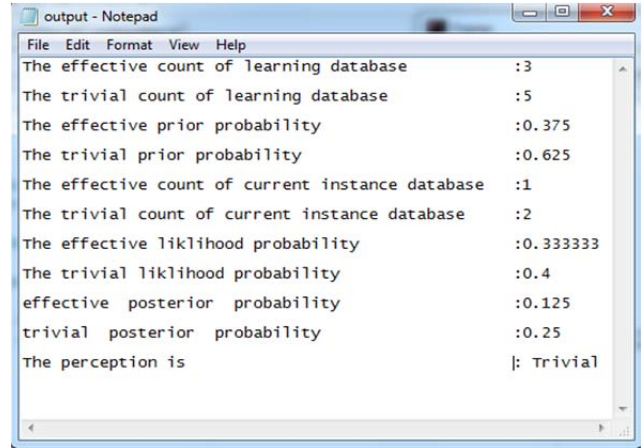


Fig. 9 Output stored file

D. Analysis

The experiment results shown in the graph of Fig. 10 clearly shows that perception classification as effective and trivial can be achieved as the success rate is very high around 90% when compared to failure rate. The graph also clearly indicates that most of the times the perception will be effective perception and at times it turns out to be trivial.

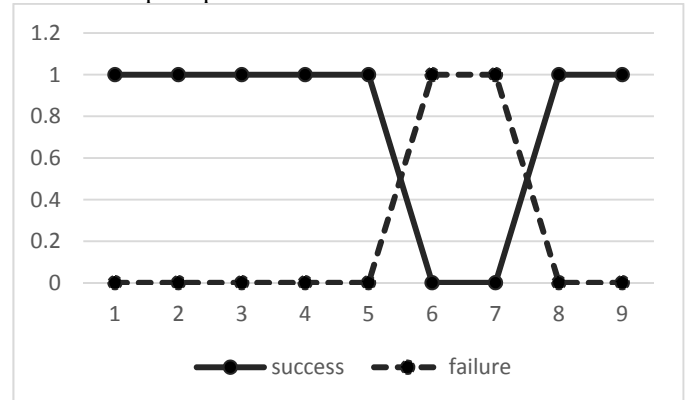


Fig. 10 Success and Failure of classification

VII. CONCLUSION AND FUTURE WORK

Perception classification is essential as it improves the cognition process. Trivial perception is an important concept in perception and in artificial intelligence. This concept can be used as an important parameter for assessing intelligence. This can also be used in robotics to enhance its perceptual ability. Here we have developed an algorithm and implemented the same. Further work can be carried forward to implement trivial perception on a robot. The robot with trivial perception should be able to demonstrate intelligence when trivial perception changes to effective perception. A better analysis can be done and find the approach to improve intelligence.

REFERENCES:

- [1] Lawrence W Barsalou, Perceptual symbol systems, Behavioral and brain sciences, (1999) 22, 577-660.
- [2] Hao Yang, Chia-Jiu Wang, Yonghong Wang, Heng-Ming Tai, Non linear Analysis in Cognition process, Proceedings of the 26th Annual International Conference of the IEEE EMBS, San Francisco USA, Sep 2004
- [3] Makoto Takahashi, Osamu Kubo, Masashi, Kitamura and Hidekazu Yoshikawa, Neural network for human cognitive state estimation, Institute of Atomic energy, Kyoto University
- [4] Dr M V Vijayakumar, A society of mind approach to cognition and metacognition in a cognitive architecture, PhD thesis
- [5] B Chandrasekaran, Multimodal Cognitive architecture : Making Perception more central to Intelligent behavior, Proceedings of the AAAI National Conference on Artificial Intelligence, 2006, pp. 1508 – 1512
- [6] Basing Perceptual decisions on the most Informative Sensory Neurons, Mirana Scolari, John T Serences, Journal Neurophysiology 2010
- [7] A. S. Rao and M. P. Georgeff, BDI Agents : from theory to practice, Proceedings of the First International Conference on Multiagent Systems, 1995
- [8] Mario A T Figueiredo, Beysian Estimation and Classification, Lecture Notes