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MACHINE LEARNING APPROACH ON EMBODIED INTELLIGENCE

[1]N. Sriharish, [2]N. Dinesh kumar, [3]S. Gowtham, [4]K. Sudha

[1] III year, Department of Computer Science and Engineering,
Muthayammal Engineering College,
Rasipuram – 637 408, India
sriharishnagarajancse@gmail.com

[2] III year, Department of Computer Science and Engineering,
Muthayammal Engineering College,
Rasipuram – 637 408, India
nvdineshkumar1997@gmail.com

[3] III year, Department of Computer Science and Engineering,
Muthayammal Engineering College,
Rasipuram – 637 408, India
gowthamselvam111@gmail.com

[4] Assistant Professor – Department of Computer Science and Engineering,
Muthayammal Engineering College,
Rasipuram – 637 408, India.
srisudhan3@gmail.com

Abstract

The field of Artificial Intelligence, which started roughly half a century ago, has a turbulent history. The machine learning techniques in this field are getting popular day by day. In the 1980s there has been a major paradigm shift towards embodiment. While embodied artificial intelligence is still highly diverse, changing, and far from “theoretically stable”, a certain consensus about the important issues and methods has been achieved or is rapidly emerging. In this non-technical paper we briefly characterize the field, summarize its achievements, and identify important issues for future research. One of the fundamental unresolved problems has been and still is how thinking emerges from an embodied system. Here, the Reinforcement learning technique is used to get the embodiment of the mind. Thinking to solve the problem reinforcement is the main learning phase in the observation and analysis of given data. The proposed system will enhance the given problems like observing the brain and its neural function clearly where the classification of collected data will be done by using k-NN algorithm and then reinforcement techniques will be used for creating embodiment of mind.

With the fundamental paradigm shift from a computational to an embodied perspective, the kinds of research topics, the theoretical and engineering issues, and the disciplines involved have undergone dramatic changes, or stated differently, the “landscape” has been completely transformed.

Key words:

Machine Learning,
Reinforcement,
k-NN Algorithm.

Introduction

The failures in traditional Artificial Intelligence (AI), largely due to the lack of rich system-environment interaction, have leaded some researchers to pursue a different avenue, the one of embodiment. With this change of orientation, the nature of the research questions also began to change. Rodney Brooks, one of the first promoters of embodied intelligence (e.g. Brooks, 1991), started studying insect-like locomotion, building, for example, the six-legged walking robot “Genghis”. So, walking and locomotion in general became important research areas, topics typically associated with low-level sensory-motor intelligence. This is, of course, a fundamental change from studying chess, theorem proving, and abstract problem solving, and it is far from obvious how the two relate to one another, an issue that we will elaborate in detail later. Other subjects that people started investigating have been orientation behavior (i.e. finding one’s way in only partially known and changing environments), path-finding, and elementary behaviors such as wall following, and obstacle avoidance.

LITERATURE REVIEW

Embodied Intelligence

The perspective of embodiment requires working with real world physical systems, i.e. robots. A crucial aspect of embodiment is that it requires working with real world physical systems, i.e. robots. Computers and robots are an entirely different ball game: computers are neat and clean, they have clearly defined inputs and outputs, and anybody can use them, can program them, and can perform simulations. Computers also have for the better part only very limited types of interaction with the outside world: input is via keyboard or mouse click, and output is via display panel. In other words, the “bandwidth” of communication with the environment is extremely low. Also computers follow clearly defined “input processing” output scheme that has, by the way, shaped the we think about intelligent systems and has become the guiding metaphor of the classical cognitivistic approach. Robots, by contrast, have a much wider sensory motor repertoire that enables a tight coupling with the outside world and the computer metaphor of input-processing-output can no longer be directly applied. Building robots requires engineering expertise, which is typically not present in computer science laboratories, let alone psychology departments. So, with the advent of embodiment the nature of the field, artificial intelligence, changed dramatically. While in the traditional approach, because of the interest in high-level intelligence, the relation to psychology, in particular cognitive psychology was very prominent, the attention, at least in the early days of the approach of embodied intelligence, shifted more towards – non-human – biological systems, such as insects, but other kinds of animals as well. Also, at this point, the meaning of the term “artificial intelligence” started to change, or rather started to adopt two meanings. One meaning stands for GOFAI (Good Old- Fashioned Artificial Intelligence), the traditional algorithmic approach.

Important goals of Embodied Intelligence

The other one designates the embodied approach, a paradigm that employs the synthetic methodology which has three goals: (1) understanding biological systems, (2) abstracting general principles of intelligent behavior, and (3) the application of this knowledge to build artificial systems such as robots or intelligent devices in general. As a result, the modern, embodied approach started to move out of computer science laboratories more into robotics and engineering or biology labs. It is also of interest to look at the role of neuroscience in this context. In the 1970s and early 1980s, as researchers in artificial intelligence started to realize the problems with the traditional symbol processing approach, the field of artificial neural networks, an area that had been around since the 1950s, started to take off – new hope for AI researchers who had been struggling with the fundamental problems of the symbol processing paradigm. Inspiration was drawn from the brain, but only at a very abstract level. In the embodied approach, there was a renewed and much stronger interest in neuroscience because researchers realized that natural neural systems are extremely robust and efficient at controlling the interaction with the real world. As mentioned above, animals can move and manipulate objects with great ease, and they are controlled by – natural – neural networks. In addition, they can move very elegantly, with great speed and with little energy consumption. These impressive kinds of behaviors can only be achieved if the dynamical properties of the neural networks are exploited. This is quite in contrast to the traditional AI approach where mostly static feed-forward networks were employed.

Early works on Embodied Intelligence

In the early phases of embodied artificial intelligence, many people were working on navigation and orientation out of a conviction that locomotion and orientation are somehow the underlying driving forces in the development of cognition, in the evolution of the brain.

MACHINE LEARNING ALGORITHMS

Supervised learning

This learning process is based on the comparison of computed output and expected output, that is learning refers to computing the error and adjusting the error for achieving the expected output. For example a data set of houses of particular size with actual prices is given, then the supervised algorithm is to produce more of these right answers such as for new house what would be the price.

Unsupervised learning

Unsupervised learning is termed as learned by its own by discovering and adopting, based on the input pattern. In this learning the data are divided into different clusters and hence the learning is called a clustering algorithm. One example where clustering is used is in Google News (URL news.google.com). Google News groups new stories on the web and puts them into collective news stories.

Reinforcement learning

Reinforcement learning is based on output with how an agent ought to take actions in an environment so as to maximize some notion of long-term reward. A reward is given for correct output and a penalty for wrong output. Reinforcement learning differs from the supervised learning problem in that correct input/output pairs are never presented, nor sub-optimal actions explicitly corrected.

Recommender systems

Recommender systems can be defined as a learning techniques by virtue of which online user can customize their sites to meet customer's tastes. For example, online user can get a rating of a product or and related items when he/she searching an items because of the existing recommender system. That is why it changed the way people find products, information, and even other people. There are mainly two approaches: content based recommendation and collaborative recommendation, which help the user for obtaining and mining data, making intelligent and novel recommendations, ethics. Most e-commerce site uses this system.

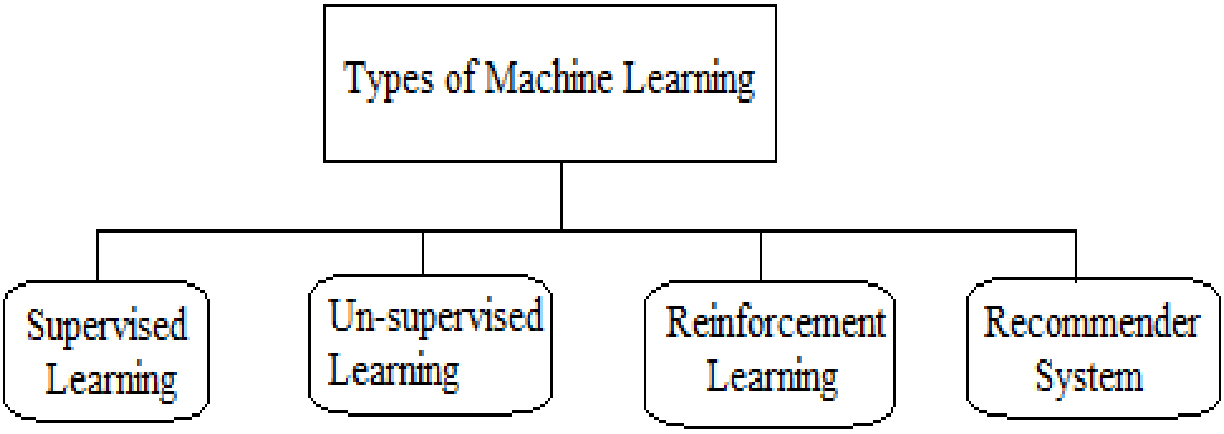

Figure 1

DIFFERENT VIEWS OF EMBODIED COGNITION

Wilson (submitted) recently distinguished between six different views of embodied cognition, of which, however, only one explicitly addresses the role of body:
“Cognition is situated”: This claim is obviously widely held in the literature on embodied cognition. Wilson herself distinguished between situated cognition, which takes place “in the context of task-relevant inputs and outputs”, and “off-line cognition”, which does not.
“Cognition is time-pressured”: That means, cognition is constrained by the requirements of real-time interaction with the environment, e.g. the ‘representational bottleneck’ (e.g. Brooks, 1991; Clark, 1997; Pfeifer & Scheier, 1999).
“We off-load cognitive work onto the environment”: Brooks (1991) formulated a similar claim by saying that “the world is its own best model”. A well-known example is Kirsh & Maglio’s (1994) study of ‘epistemic actions’ in the game of Tetris, i.e. decision-preparing movements carried out in the world, rather than in the head.
“The environment is part of the cognitive system”: An example of this view could be Hutchins’ (1995) work on distributed cognition, in which, for example, the instruments in a cockpit are considered parts of the cognitive system. However, as Wilson points out, “relatively few theorists appear to hold consistently to this position in its strong form”.
“Cognition is for action”: A claim made, for example, by Franklin (1995), who argued that minds are the control structures of autonomous agents. • “Off-line cognition is body-based”: According to Wilson, this claim has so far received least attention in the cognitive science literature, although “it may in fact be the best documented and most powerful of the six claims”. Perhaps the most prominent example is the work of Lakoff & Johnson (1980, 1999) who have argued that abstract concepts are based on metaphors grounded in bodily experience/activity. This claim is discussed in further detail in the following section.

Level (Symbol)	Typical Activity	Typical Questions	Examples
1. Association $P(y\|x)$	Seeing	What is? How would seeing X change my belief in$Y$?	What does a symptom tell me about a disease? What does a survey tell us about the election results?
2. Intervention $P(y\|do(x), z)$	Doing	What if? What if I do X?	What if I take aspirin, will my headache be cured? What if we ban cigarettes?
3. Counterfactuals $P(y_x\|x', y')$	Imagining, Retrospection	Why? Was it X that caused Y? What if I had acted differently?	Was it the aspirin that stopped my headache? Would Kennedy be alive had Oswald not shot him? What if I had not been smoking the past 2 years?

Table 1

MACHINE LEARNING APPROACH

In the following section we discuss the supervised classification algorithms that we used in order to recognize sentiments in texts which can be learned by the robots and analyse all the texts clearly. The first two machine learners use feature vectors with numerical values, the last classifier only considers binary feature values.

Support Vector Machine (SVM)

A Support Vector Machine (SVM) (Cristianini and Shawe-Taylor 2000) operates by constructing a hyperplane with maximal Euclidean distance to the closest training examples. This can be seen as the distance between the separating hyperplane and two parallel hyperplanes at each side, representing the boundary of the examples of one class in the feature space. It is assumed that the best generalization of the classifier is obtained when this distance is maximal. If the data is not separable, a hyperplane will be chosen that splits the data with the least error possible. An SVM is known to be robust in the event of many (possibly noisy) features without being doomed by the curse of dimensionality and has yielded high accuracies in sentiment classification (e.g., Pang et al. 2002). The Weka6 implementation was used.

Multinomial Naive Bayes (MNB)

A Multinomial Naive Bayes (MNB) classifier (Manning et al. 2008) uses Bayes rule as its main equation, under the naive assumption of conditional independence: each individual feature is assumed to be an indication of the assigned class, independent of each other. An MNB classifier constructs a model by fitting a distribution of the number of occurrences of each feature for all the documents. We selected this classifier because of its simple implementation, its computational efficiency and a straightforward incremental learning. We used the MNB classifier of Weka.

Maximum Entropy (ME)

A Maximum Entropy (ME) classifier (Berger et al. 1996) tries to preserve as much uncertainty as possible. The models that fit the training examples are computed, where each feature corresponds to a constraint on the model. The model with the maximum entropy over all models that satisfy these constraints is selected for classification. We choose to work with an ME classifier because in information extraction from natural language texts, this classification algorithm often yields very good results, as it can deal with incomplete information in a very elegant way. When classifying natural language utterances the training examples seldom cover all variant linguistic expressions that signal certain semantics. The Maxent7 package from OpenNLP was used as implementation..

k-Nearest Neighbor (k-NN)

k-NN (k-Nearest Neighbor) classifier is the best classifier to compare the results and produce the better prediction and results. To make it really simple *k*-nn works on the paradigm that if k instances of same class "look" like the current instance then it is highly likely that object class is same as that of those k instance. Formalizing this k-nn classification finds a group of k objects in the training set that are closest to the test object, and assigns the test object a class on the basis of predominant class in its neighborhood. The below picture shows the algorithm in a detailed manner. Training data will be given as input and we get the class of trained data.

Input : D, the set of training objects, the test object, $\mathbf{z}$, which is a vector of attribute values, and L, the set of classes used to label the objects

Output : $c_z \in L$, the class of z

foreach object $\mathbf{y} \in D$ **do**

| Compute $d(\mathbf{z}, \mathbf{y})$, the distance between $\mathbf{z}$ and $\mathbf{y}$;

end

Select $N \subseteq D$, the set (neighborhood) of k closest training objects for z;

$c_z = \underset{v \in L}{\operatorname{argmax}} \sum_{y \in N} I(v = class(c_y))$;

where $I(\cdot)$ is an indicator function that returns the value 1 if its argument is true and 0 otherwise.

Figure 2

Out of these algorithms mentioned above kNN classifier is better and produces the accuracy of 93.7%.

DEEP LEARNING APPROACH USING NEURAL NETWORKS

Hawkins believes that the brain learns by interacting with its environment. The classic Deep Learning training procedure is one of the crudest teaching methods that one can possibly imagine. It is based on repetitively and randomly presenting facts about the world and hoping that the student (i.e. the neural network) is able to disentangle and create sufficient abstractions of the world. One should at least be able to do better by having a curriculum. That is, to present training data that starts easy and then scaling it up to more difficult training. We actually see curriculum learning effectively used in the form of the latest StackGAN architectures. This is where smaller problems are tackled first and the network is incrementally resized to tackle even larger problems. However, biological beings learn quickest by allowing them to interact with the environment. In other words, rather than just having a teacher who defines a rigid curriculum, one allows the student to drive their own exploration of the teaching material. There is no better way to learn a new subject than to allow the student a way to interact with the subject and to discover its responses. This is exactly what we see in the advances in cognition that DeepMind has exhibited in its AlphaGo Zero and Alpha Zero game playing machines. If you can set up a teaching environment that adjusts to the capabilities of the student, then the student can comfortably walk up a staircase toward richer understanding.

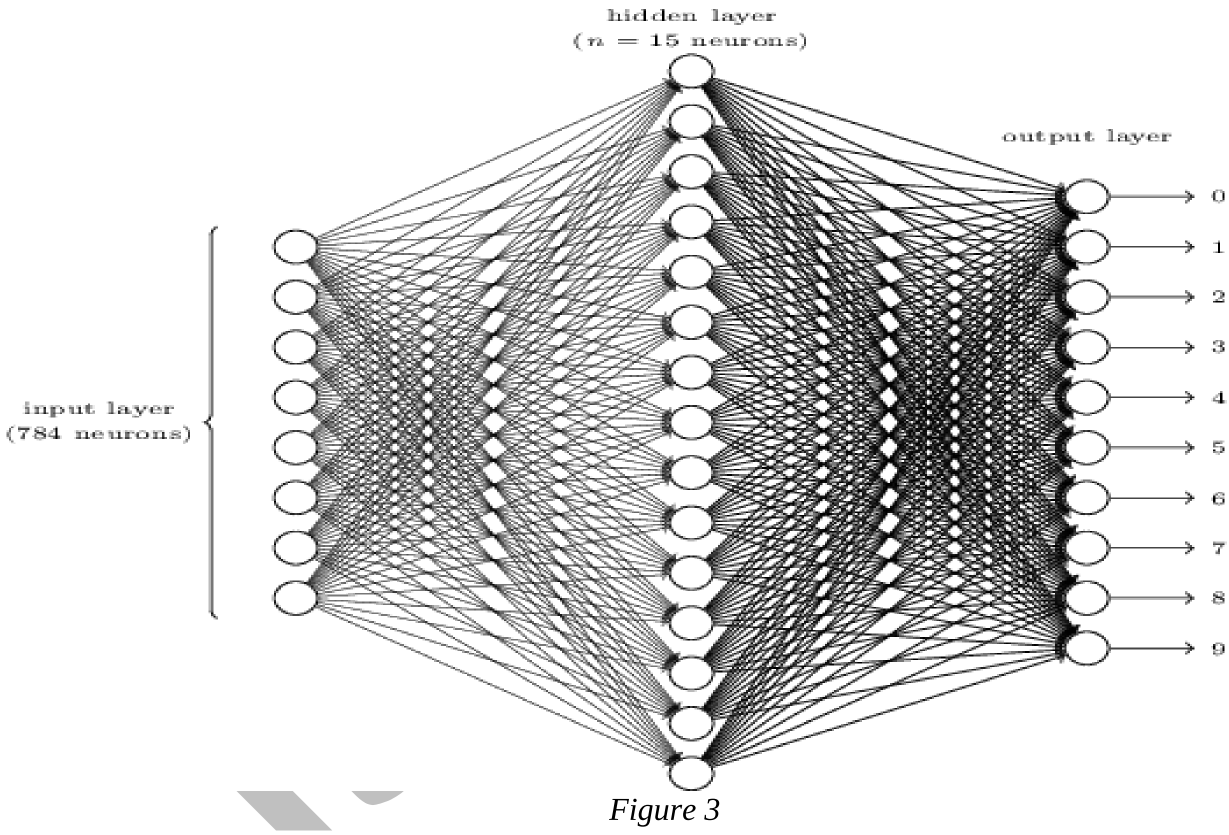

Figure 3

In the above diagram, the neural network is used to get the collection of data and it is used to process the input from the biological inputs from the brain to simulate different outputs and better output will be generated from the network. So, that robot will learn from the different outputs to create a new scheme for different inputs and it will enhance the classical machine learning technique.

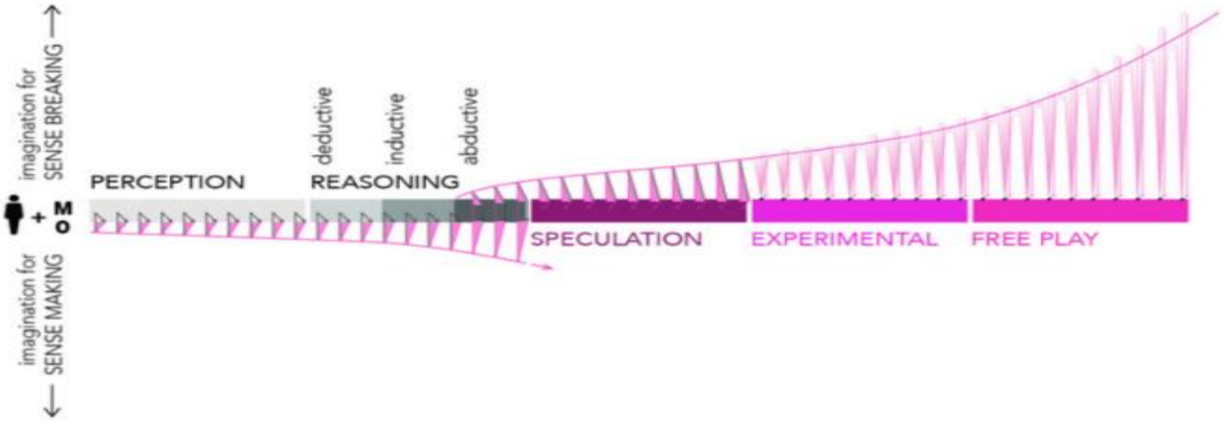

Figure 4

Result of the network will be gradually increased for different level of inputs to get the all abilities like human is graphed in the above diagram.

Conclusion

However, it is important to keep the long-term visions in mind when thinking about the next steps. The difficulty of research in any field, but in particular in artificial intelligence is to map the big visions and challenges onto concrete, doable steps.
We found out that machine learning approach will be used primarily for low level inputs and it produce the effective results. But for more complex inputs, the advanced machine learning techniques like Deep Learning is used. The embodied intelligence can be achieved through some advanced researches given by Dr .Ziemke.

This way, the ideas that embodied artificial intelligence has taken into account and will spread to numerous scientific and technological areas for the benefit of society.

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