



MACHINE LEARNING USING CHUNKING

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ABSTRACT

Research on learning in computing system is a popular topic in artificial intelligence. There is a need of incorporating learning mechanisms in computing system. When this same problem is solved again, it again requires similar efforts and time or more may be but when a problem is solved using learning agents, they learn the procedure of solving the problem so that when similar problem came again learning reduces the efforts and time required to solve it. There are many methods available for learning i.e., episodic learning, semantic learning, reinforcement learning and learning with chunking. Chunking is a learning mechanism for problem solving based on its past experiences. In chunking chunks are formed; these chunks can be used in similar situation in future. In this way chunking enhance the performance of intelligent system.. In this paper chunking is used to explain the benefit of learning mechanism in soar software to solve block world problem.

Keywords: *Block World Problem, Episodic Learning, Learning With Chunking, Machine Learning, Reinforcement Learning, Semantic Learning.*

I INTRODUCTION TO MACHINE LEARNING

Machine learning is a type of artificial intelligence (AI) that provides learning ability to the computer without being easily programmed. This will focus on the development of computer programs that can teach themselves to change and grow when exposed to new data. Machine learning detects pattern in data and adjust program according to the actions. A machine learning algorithm differs from both supervised and unsupervised learning by how it interprets inputs. Illustrate their difference by describing what they learn about a “thing.”Supervised algorithms can apply what has been learned in the past to new data. Unsupervised algorithms can draw inferences from datasets.

Machine learning is a core subarea of Artificial intelligence. Machine learning is a type of learning in which we teach machines how to learn automatically whenever a new data arises. Without machine learning we will not be able to build a fully intelligent system as it will not learn things automatically to repeat them whenever required in future. For example: many automatic machines like ATM, many medical machines, military machines can do no work without learning. We would not consider a system to be truly intelligent if it is incapable of learning since learning is at the core of intelligence. Our goal is to devise learning algorithms that do the learning automatically without human assistance. [1]



1.1 Advantages of machine learning

- 1.1.1 It is automatic and ubiquitous.
- 1.1.2 It is task independent and fixed.
- 1.1.3 It is only single experience based.
- 1.1.4 Human concern is not needed. [2]

II METHODS OF MACHINE LEARNING

The ability to learn and improve is essential for an intelligent system and on the basis of this we have four types of learning.

- 2.1 Episodic learning
- 2.2 Semantic learning
- 2.3 Reinforcement learning
- 2.4 Learning with chunking

2.1 Episodic learning

It contains information about specific events by capturing a history of what happened to the entity in past, in form of snapshots. Episodic learning learns all these snapshots in a chronological order that can be retrieved from episodic memory whenever needed in future. Episodic learning enhances the reasoning and learning capability of an intelligent agent. Embedding episodic learning in intelligent agent enables many advanced cognitive capabilities such as virtual sensing, internal simulation and prediction, retrospective reasoning and learning etc. [3]

2.2 Semantic learning

It includes about what you already know about the world. In semantic learning general facts about the world are learnt such as chair has four legs. Semantic learning includes only true and relevant information about the object for example it learns and stores the structure of agent that originates in working memory but relevant for some future conditions. Semantic learning increases our ability to develop agents that reason and use general knowledge about the world. [4]

2.3 Reinforcement learning

It allows the intelligent agents to improve their decision making as it receives reward from the environment. It is a learning mechanism that uses reward as a source of knowledge to enhance performance of an agent by adjusting the selection of action in rules. Reward can be positive or negative based on its performance. It is a type of learning from its environment, without the need of specific training. [5]

2.4 Learning with chunking

It is a simple experience based learning mechanism to solve a problem. Chunking was first proposed by Miller in model of human theory and has since become an important component of machine learning. Chunking is a process of creating chunks (new rules) which within contains the group of several other chunks. [6]

III MACHINE LEARNING WITH CHUNKING

Chunking is one of the learning methods of machine learning which learns from its experience to enhance the performance of an intelligent system. An intelligent system acquires knowledge using chunking mechanism. When the system has insufficient knowledge to solve a problem it arises an impasse at that point and to resolve that impasse a subgoal is created. Whenever a result is produced in subgoal, chunks are produced. Chunks are nothing but new production, forms when small steps of a task are grouped into larger steps of task. Once a chunk has been learnt the results of an impasse can be directly applied by firing a chunk if the same situation occurs again and in this way chunking speeds up problem solving. [7]

3.1 Illustration of chunking with the help of an example:

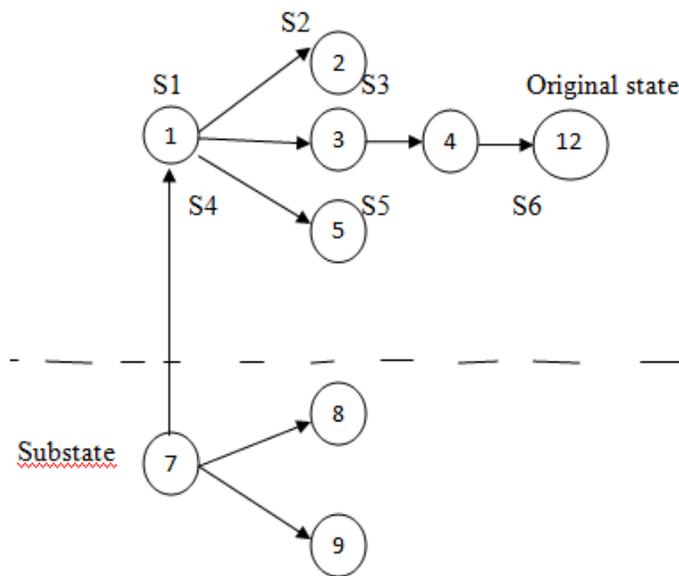


Fig: 1(a)

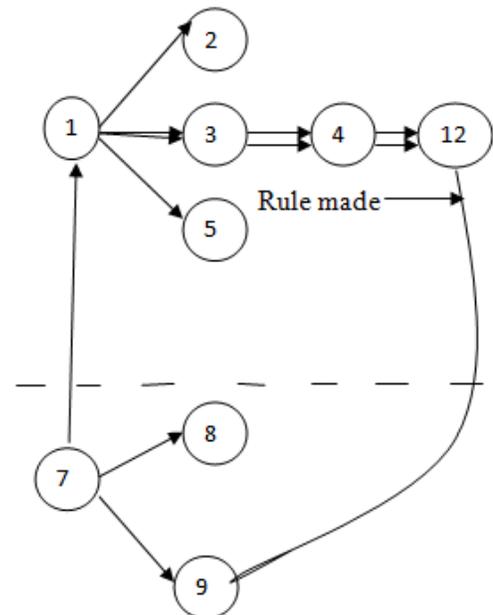


Fig: 1(b) ... [8]

In fig 1(a), we can see that memory elements are named with numbers as 1,2,3,...so on, a dotted line in between is to differentiate between original state and substate. A substate is created whenever an impasse arises in original state at that time a further progress cannot be made. According to fig 1(b), here S1 is the initial state and S6 is the final state. To reach at goal state there are number of paths provided and hence a preference is to be made among these paths. but for S2 and S5 state there are no memory elements further to reach at goal state so, preference is given from S1 to S3 state and then from S5 to S6 state. So, we will attempt to make a path which is more accurate and estimates the chances to reach the goal state S6.

Whenever an impasse arises in original state a substate is formed. As the result produced in original state, substate will justify the result by making a rule and once a rule (chunk) is learnt then whenever the same conditions will

match with new structures in working memory then this rule will fire and executes the action to create goal state directly.

IV SOLVING BLOCK WORLD PROBLEM USING CHUNKING

Block world planning appears to solve many difficulties of systems where goal is to manage blocks in lesser time.

4.1 Block world problem statement

‘‘We have three blocks naming A, B and C placed order less on a table. The operators move one block at a time to another location and the goal is to build a tower with A on top, B in the middle and C on the bottom. The initial and final states are illustrated below in fig: 2’’. Our objective in a block world problem is to place blocks from initial state to desired state in less number of steps by moving one block at a time from start to goal state. [9]

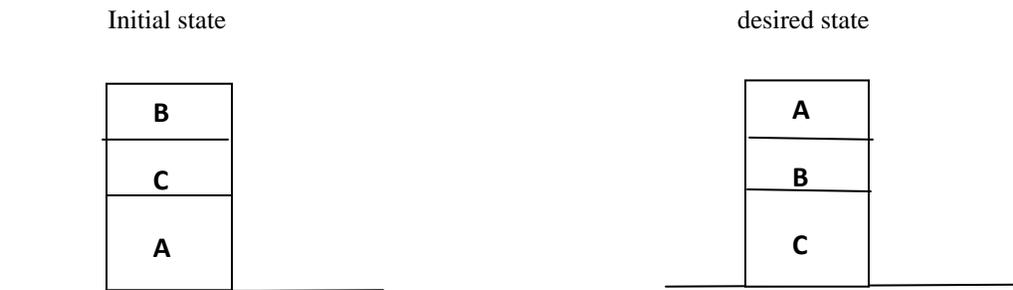


Fig: 2 Initial and Final state of Block world problem

4.2 Solving problem using chunking

S is a state

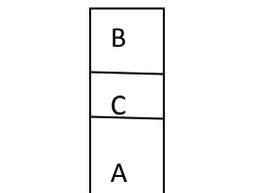
O is an operator. The operator in this task move a single block from its current location to a new location. Each operator is represented with the following information:

4.2.1 The name of the block being moved

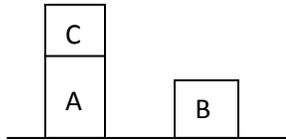
4.2.2 The current location of the block

4.2.3 The destination of the block

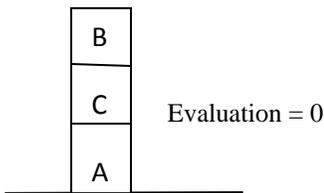
Step1 (initial state)



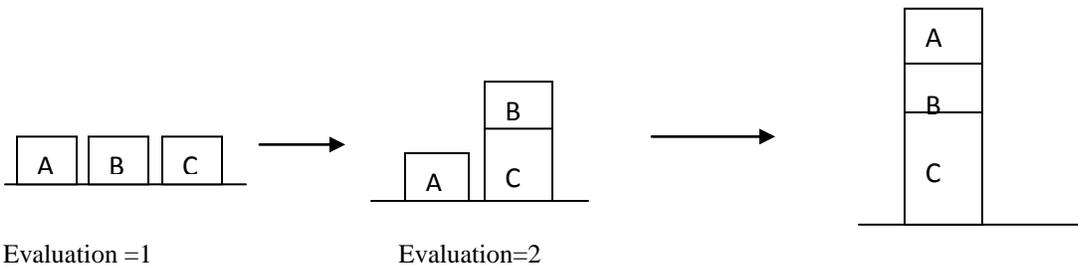
Step 2 (Tie impasse)



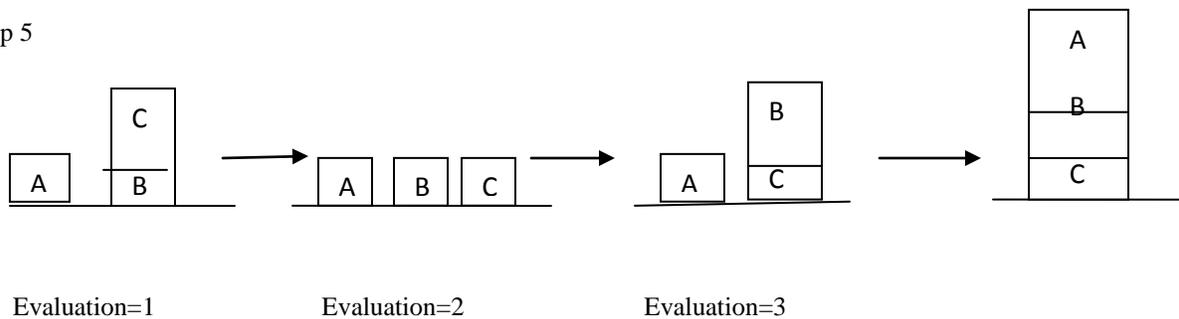
Step 3 (return to original state)



Step 4



Step 5



We have provided initial state in block world problem- (before any operators have been proposed or selected) illustrated in step 1. In step 2 we make our required move by placing block B on table which arises an impasse at this point. Now we have three ways to solve this problem which we are explaining in step 3, step 4 and step 5 respectively. If we prefer step 3 to other two, there will be no progress and the current state will be returned to the original state so, there is no need of going this way. If we prefer step 4 to step 5 than we have to do two evaluations by changing the state of blocks two times and then we will reach at goal state. If we prefer step 5 to step 4 then we



have to make three evaluations by changing the state of blocks three times so it will take more time to reach at a goal state.

V ALGORITHM FOR BLOCK WORLD PROBLEM USING CHUNKING

Initial state is....

S: [(on A, table) (on C, A) (on B,C)]

O: move block (B, table)

S: [(On C, A) (on A, table) (on B, table)]

Tie impasse: move block (B, C), move block(C, table), move block(C, B)

O: evaluate (move block B, C)

S: [(on A, table) (on C, A) (on B, C)] (Original state)

O: evaluate [move block(C, table)]

S :[(on A, table) (on B, table) (on C, table)]

O: move block (B, C)

S [(On A, table) (on B, C) (On C, table)]

O: move block (A, B)

S: [(on C, table) (on B, C) (on A, B)]

Result: evaluation=2

O: evaluate [move block(C, B)]

S: [(On A, table) (on C, B) (on B, table)]

O: move block(C, table)]

S: [(on A, table) (on B, table) (on C, table)]

O: move block (B, C)

S [(On A, table) (on B, C) (On C, table)]

O: move block (A, B)

S: [(on C, table) (on B, C) (on A, B)]

Result: evaluation=3

End [10]

Rules are learned for all the results that are created including the preferences created in the substates that arise from the tie impasses. The valuation is computed on the basis of the distance to the goal, so a smaller evaluation is better.

[10]

Our final result is obtained from two evaluations, thus with chunking block world problem can be solved in less steps.



6.3 Explanation of figures

To see how effectively chunking agent work in block world problem, results can be inferred from above observation table and bar graph (fig 3), we can see that when there is no machine learning than agents give results in large number of steps approx. 55 steps and when we solve the given block world problem with machine learning using chunking agent it give results in altered steps automatically i.e., approx 11 steps after 20 trials. To simulate the learning soar software is used and the problem of block world is being solved using one of learning mechanisms. So learning with chunking has reduced the processing time of a problem in an efficient way.

VII Conclusion

Learning is very important for intelligent machines. Learning is a dexterous method to solve a problem efficiently and in less time. In this paper, chunking (a method of learning) is used to solve block world problem and we have solved it by making less moves and less evaluations. An algorithm is written to observe block world problem solution with learning and a table is made to show the average steps that have reduced with learning hence chunking is a profitable method of learning for intelligent systems.

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