APPLYING Q-LEARNING TO NON-MARKOVIAN ENVIRONMENTS

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Abstract: This paper considers the problem of intelligent agent functioning in non-Markovian environments. We advice to divide the problem into two subproblems: just finding non-Markovian states in the environment and building an internal representation of original environment by the agent. The internal representation is free from non-Markovian states because insufficient number of additional dynamically created states and transitions are provided. Then, the obtained environment might be used in classical reinforcement learning algorithms (like SARSA(λ)) which guarantee the convergence by Bellman equation. A great difficulty is to recognize different "copies" of the same states. The paper contains a theoretical introduction, ideas and problem description, and, finally, an illustration of results and conclusions.

1 INTRODUCTION

One of the most topical tasks of artificial intelligence is searching for optimal policy of interaction with an environment by autonomous intelligence software agent. Classical methods of reinforcement learning are performing successfully in the so-called Markovian environments. In this work the idea and implementation approach are stated for non-Markovian environments. The approach offered represents a method of training based on reinforcement learning. Thus it is important to preserve the properties and advantages of the classical algorithm of reinforcement learning and its condition of convergence.

2 AGENT TASK AND ENVIRONMENT

Reinforcement Learning (RL) is defined as the problem of an agent that learns to perform a task through trial and error interaction with an unknown environment which provides feedback in terms of numerical reward (Butz). The agent and the environment interact continually (see Figure 1) within discrete time. The experiments are carried out in a well-known task - searching for a path in labyrinth (kind of agent control), in other words, building an optimal policy (strategy) of actions by exploration of the environment. The reason for our choice is obviousness and simple understanding of the received results. SARSA(λ) learning algorithm [Sutton] is preferred as a base learning algorithm, which will be combined with the investigated algorithms.

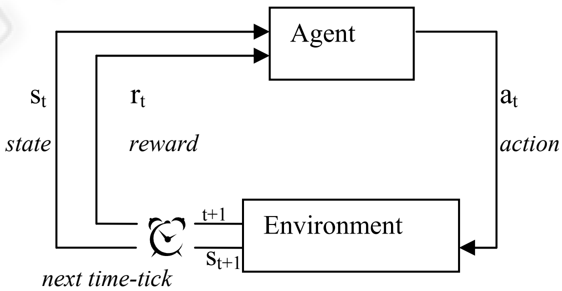

Figure 1: Agent-Environment interaction.

Let's consider the static cellular world - a labyrinth. Each cell of the labyrinth is either free for agent pacing, or occupied by some static obstacle. One of the cells contains food (sometimes called target cell or goal cell). In our case, the goal cell is labelled by letter G. An example of simple grid world is depicted in Figure 2.

To make the grid world usable like the environment, we must define a set of data which represent the state of the agent. Usually the state is

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all the information available to an agent that is provided by its sensors. The set of agent sensors (according to available information) depends on task conditions. In our case the agent possesses only four sensors: s_S, s_E, s_W, and s_N ; each of them returns value 1, if the obstacle is detected in a neighbor cell, in the corresponding direction, otherwise value 0. Thus, agent state might be expressed in binary form, where each bit corresponds to each sensor. For example, if the obstacle is North and East directions, then state in binary form will be equal to $S = 0101_2$. For further calculation convenience, it is better to convert the binary value to decimal form:

$$S = 0101_2 = 0 \cdot 2^3 + 1 \cdot 2^2 + 0 \cdot 2^1 + 1 \cdot 2^0 = 5_{10}$$

Thus, on each step by getting values of sensors the agent can compute the current state by formula 1:

$$S = 8 \cdot s_{South} + 4 \cdot s_{East} + 2 \cdot s_{West} + s_{North} \qquad (1)$$

The value obtained is the state of the agent. Only 16 different states are available in our task (including zero state interpreted as the absence of obstacle around). Figure 2 depicts the grid world with calculated values for each cell (state).

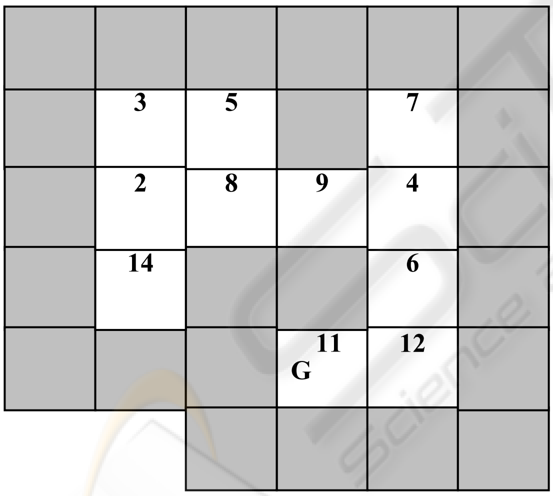


Figure 2: Grid world with evaluated states for each cell.

The agent can choose from four actions: to step only one cell in each of four directions. It is important to point out that each action of the agent is surely executed. In other words, if in a previous state s action a was applied, the probability of obtaining next state s' is equal to one: P(s, a, s') = 1. If we wish to use a probabilistic model for defining probabilities of transitions, it requires including additional 3-dimensional table.

Having a set of state, actions and probability of transition, the grid-world-like environment now might be represented in the transition graph form which is often used for representing the Markovian processes (Russell):

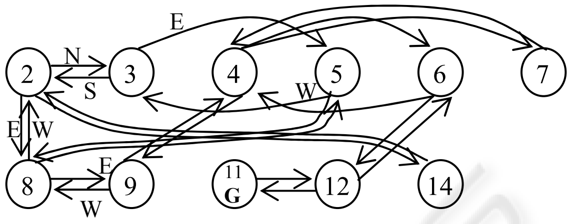


Figure 3: Agent environment in the graph form (states and transitions form).

The arrows denote possible transitions through implementing corresponding actions (moving north, east, south and west). It is important to point out that the grid world form is the form which is closer to the real world form and keeps more properties than the graph form. The graph form is a model which only keeps information sufficient enough to the agent. For example, looking at the grid world we can see why a transition from one cell to another is available. In graph mode we have only the fact of available transitions. The reason might be interpreted as additional information available for operation. In our case the essential difference between two forms is the properties that belong to the nature of cell. Additional existence and the number of non-Markovian states depend on the precision of external world reproduction. Moreover, the number of non-Markovian states might be reduced by involving eight sensors instead of the existing four. So, the graph representation is less attractive than other forms; nevertheless it is worth detailed consideration because of its representation of state-action model, which is used in reinforcement learning algorithms. In Table 1 the main difference between grid-world form and graph form is shown.

Two last distinctions cause the greatest interest. These distinctions raise three fundamental problems in the task of agent control in non-Markovian environments:

1) detection of non-Markovian states;
2) detection of states with inconstant transition;
3) agent learning and its ability to distinct different copies of the same states.

Table 1: Difference between two forms of environment representation.

Grid world form	Graph form
• The coordinate system in the labyrinth is caused by the conception of cell	• there is no conception of a cell, thus absence coordinates
• Transitions move the agent through cells	• transitions move the agent from one state to another
• The obstacles and cells arrangement describes the actions execution ability	• there are no reasons that could describe the ability of executing actions
• equally valued state cells are different copies of the same state	• there is no conception of the same state copies ,instead of that the non-Markovian conception or inconstancy of transition takes place.

3 THE SENSOR SIGNALS INTERPRETING PROBLEM

As was mentioned above, in task of building optimal policy through exploring non-Markovian environment three problem cases might be revealed.

Case 1. The case supposes that from some state at different moments of time it is necessary to execute different actions. In other words, the current state does not fully define the next action (Russell) (Lin). This case is called non-Markovian state. The *Woods101* environment is a classical example of such case (see Figure 4) (Kwee).

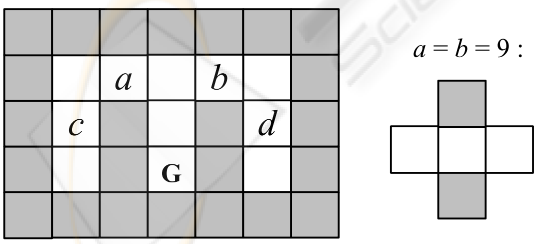


Figure 4: Left: Non-Markovian environment Woods101, Right: an example of ambiguous state.

The cells denoted *a* and *b,* correspond to the same state because of their equal values evaluated upon agent sensors signals. Having appeared in that state the agent sometimes is compelled to move east, but sometimes west. Thus, having only current state's information, the agent is not capable of making a decision and defining the optimal action.

Case 2 is the evolution of the previous and consists of taking the same action from the same state at different times, and the different reaction of environment is observed. Let's call this case the transition inconstancy. Let's see cells *c* and *d,* for example. Again, each of them represents the same state. An attempt to move north will lead to different future states (see Figure 5).

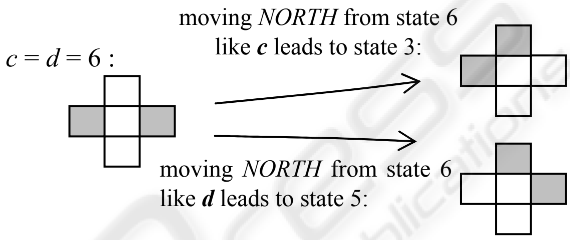


Figure 5: Example of inconstant transition from state 6.

Case 3 relates to the problem of interpreting the return of the same state (equal to source state). Let's consider state «9» depicted in Figure 6 (left). While the agent is trying to move north, it meets the obstacle, so, the environment returns agent to the source (previous) state, which equals «9». Thus, two ways of interpreting the situation are appropriate: 1) the agent was returned to the source state (see Figure 6, right), or 2) the agent was moved to another copy of the same state (like moving west or east, see Figure 6, left). Different interpretations of states are possible: either we do not take sensors nature in account or instead of sensors methodology the special channel for already evaluated state transmitting is used. If the agent "understands" the sensors meaning, it might be used as additional signs. These signs might be sufficient to distinguish different copies of the state. The model and agent-environment conditions interaction are defined by the task.

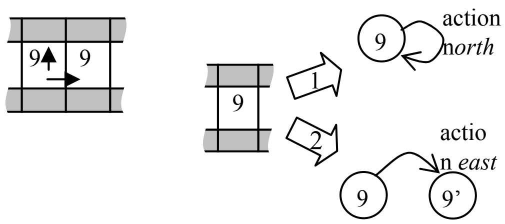


Figure 6: Left: fragment of an environment; Right: two ways of interpretation.

The problem of distinguishing two equal states is connected to that of representing same states in a graph form or Markov chains. Should we duplicate state «9» or leave it unique but having multiple connections to neighbours? In its turn, there should be «return links» which are responsible for agent returning in source state in case of bumping to obstacle.

4 SOLUTION

The idea of the solution in short is to build internal *Markovian* representation of external non-Markovian environment in parallel with learning process. The solution includes the following tasks:

1) the problem of detecting non-Markovian states and inconstant transitions;
2) the problem of conversion of ambiguous states to Markovian states, more specifically:
   a. problem of distinguishing exemplars of same states;
   b. problem of building internal representation of the environment.
3) problem of agent learning and functioning in external non-Markovian environment through internal Markovian representation.

Hence, the implementation supposes the following steps:

1) Develop an algorithm for detecting ambiguous states.
2) Develop an algorithm for converting external states to internal.
3) Slightly modify the existing Q-learning algorithm for learning and controlling the agent in internal environment.
4) Execute a number of experiments in most famous non-Markovian environments, like Woods101, Woods102, Maze5, Maze6, Maze7, Maze10 etc.

The general interaction architecture is depicted in Figure 7. The architecture is based on the agent-environment interaction model described in (Russel) and (Padgham). It is important to point out that the involved Sarsa(λ) algorithm (mentioned in (Sutton) remains the same. It is necessary to guarantee the convergence of algorithm. Only inessential modifications are applied.

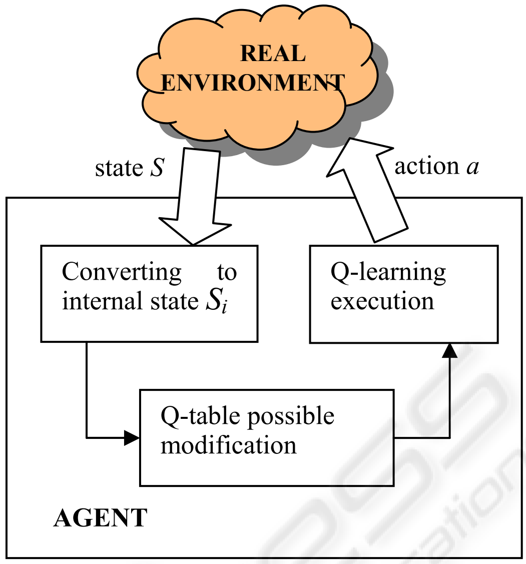


Figure 7: The general process.

4.1 The Indication of Ambiguous State and Algorithm for its Detection

Non-Markovian states and states with inconstant transition due to their common nature have common simple indication: if transitions are observed when the agent is moved from state s to different target states by action a, then source state s is ambiguous. A simple example is shown in Figure 8.

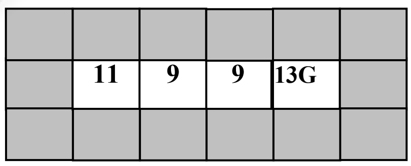


Figure 8: A simple example with ambiguous state «9».

During environment exploration, the agent finds out that applying of action «step east» being in state «11» always moves him to state «9». In its turn, application of action «step east» being in state «9» sometimes moves it to state «9» and sometimes to state «13». Such an uncertainty makes the building of the Q-table more difficult. The formal indication of ambiguous state might be expressed as follows:

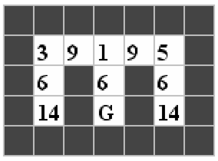
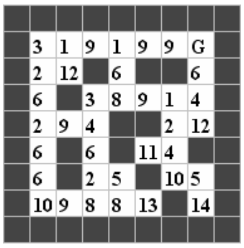
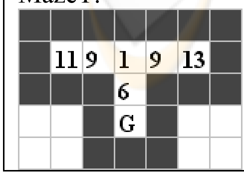
$$(s_i, a_j)^t : s^{t+1} \neq (s_i, a_j)^{t'} : s^{t'+1}, \qquad (2)$$

where $(s_i, a_j)^t$ and $(s_i, a_j)^{t'}$ are same corteges observed at different moment of time, S^{t+1} and $S^{t'+1}$ - states returned by the environment (through sensors) at next time tick.

Ambiguous state detection is executed within the framework of Q-learning cycles and requires only additional table size SxA for keeping observable transitions. Each cell [s,a] keeps target state *s'*. As soon next observation brings different target state, the source state *s* is marked as ambiguous.

It is important to point out that the indication does not require knowing of the goal state. Ambiguous states detection occurs while Q-learning builds its policy; it does not require special exploration steps of the agent. For experiments the algorithm was executed on a set of MacCallum's mazes and other environments. A short analyzing log for each environment is presented in Table 2.

Table 2: Founded ambiguous states.

Maze	Founded ambiguous states (state:action)
Woods101: 	(6 :↑) (9: →) (9: ←)
Maze5: 	(1:→); (1:↓); (1:←); (2:→); (2:↓); (2:↑); (3:→); (3:↓); (4:←); (4:↓); (4: ↑); (5:←); (5:↓); (6: ↑); (6:↓); (8:→); (8:↑); (8:←); (9:→); (9:←); (10:→); (10:↑); (12:↑);
Maze7: 	(6:↑); (6:↓);
MazeT: 	(9:→); (9:←);

For the environment depicted in Figure 2 no ambiguous states were detected. This result is true.

4.2 Making Internal Representation of the Environment

Having a method for detecting ambiguous states, it is time to build the internal representation. The L-table (log) is used for storing the internal representation of the environment. At the same time, L-table is used for detecting ambiguous states. Each row corresponds to a state. The columns represent actions. For each action two columns are reserved. The first column keeps the previous state. The second one keeps next state. In the table below an example of L-table is given.

Table 3: Example of L-table.

State	Departure state				Arrival state			
	n	e	s	w	n	e	s	w
1		9		16		16	14	9
9		11		1		1		11
11				9		9		
13		16						16
14			1					
16 |9		1		13		13		1

The L-table was built by the agent and contains the internal representation of the environment depicted in Figure 9.

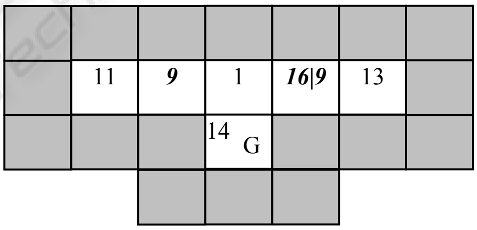


Figure 9: Environmet with internal state «16».

The visible symmetry of L-table is only possible in the task having contrary action like stepping left and right or up and down, etc. To describe the process of the table formation, let us consider state 1 in detail. Each "Departure state" means the state where appropriate action was applied by the agent with the following move to the current state 1 (row 1) Each "Arrival state" means the state, in which agent will be moved after applying the appropriate action from the current state 1. Actually, the L-table is a form of memory (of depth one) storing the applied action. The L table is filled by the agent through the exploring of the environment. The algorithm requires preliminary examination of the problem of distinguishing exemplars of same states.

4.3 Distinguishing of Exemplars of Same States

The main purpose of the internal representation is to obtain dynamically created states. These states represent each exemplar of the same original state as a new state. In the L-table a new state is generated if in filling the L-table a collision of states storing occurs. For example, for the action east of state «9» two destination states are possible: «1» and «13». As soon as the collision appears, the new state will be prepared and included in the table. In our case the state «16» is descendant of state «9». Moreover, the new state «16» inherits all appropriate transitions.

At the same time there arises a problem of recognizing internal state having original external state. The problem is solved by comparing the transition history for one last step with the L-table. If the L-table is not filled or filled partially, then methods of random or directed selection are applied. The algorithm under consideration is described below. It is based on the original algorithm Sarsa(λ) [Sutton]. The presentation is kept original. Only the bold style is used to highlight the modifications made and new elements introduced.

```
Initialize Q(s,a) arbitrarily and
               e(s,a) = 0, for all s,a
Repeat (for each  episode):
   Initialize s, a, si
   Repeat (for each step of episode):
      Take action a, observe r, s´
      s´i = GetInternal(si, a, s´)
      IF  isTransitionFickle then
         Expand tables L, Q, e
         s´i  is new one
      Choose a´ from s´i using e-greedy
      δ ← r + γQ(s´i,a´) – Q(si,a)
      e(si,a) ← e(si,a) + 1
      for all si,a :
         Q(si,a) ← Q(si,a) + α δ e(si,a)
         e(si,a) ← γ λ e(si,a)
         si ← s´i; a ← a´
      Update table L
until si is terminal
```

The denotation of variables is also kept original, only s_i and s'_i are internal mappings of appropriate states. As can be seen, the changes are related to involving the mechanism of internal representation and Q-table adaptation. The key procedure GetInternal() returns internal state according to table L:

```
Input parameters: si, a, s´
Creating of list of descendant states
of s’
Searching of equal transition entries
Possible cases:
  No entries: return external state
  One entry: return it
  Several entries:
    applying methods of random or
directed search.
```

In case of several entries the incorrect internal state might be returned. This situation is similar to action testing in reinforcement learning: incorrect returns will disappear. Application of an algorithm like bucket brigade might be helpful in this case.

5 CONCLUSIONS

The proposed modified Sarsa(λ) algorithm implements the idea of environment internal representation. The modified algorithm is able to recognize ambiguous states. Nevertheless, it suffers from the lack of recurrent mechanisms to cope with difficult mazes like Maze5 due to similar sequences of transitions. The success of applying it on simple mazes like Woods101, Maze7, MazeT demonstrates the ability of the agent to build the internal representation of the environment and use it in reinforcement learning instead of original algorithm. An interesting direction for further research is to upgrade the algorithm to enable it to cope with complicated environments. Future research will also address the formalisation and generalisation of the algorithm discussed

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