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Research Article

Basic Research on Transfer Learning Indicators for Reinforcement Learning

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ABSTRACT

Reinforcement learning requires a lot of time for the agent to learn. Transfer learning methods can be used to shorten this learning time, but they have the disadvantage that it is not known which knowledge is effective in what kind of environment until it is learned. When users transfer knowledge, it is necessary to investigate the relationship between the transfer source and the transfer destination. This study proposes an adaptive criteria evaluation index that can determine this relationship in advance. In the simulation, we confirmed the effectiveness of the proposed method using several problem examples.

1. Introduction

Machine learning is rapidly developing and has produced results in various fields such as natural language processing and image processing. Reinforcement learning [1], [2], which allows self-learning, is applied in all fields. Reinforcement learning has the disadvantage that it takes time to learn because the agent learns from scratch in a new environment through trial and error. A large number of studies have been carried out on learning time reduction methods, one of which is transfer learning. Transfer learning is a method of adapting and reusing content previously learned from similar tasks to new tasks. Since there is no need to re-learn, the learning time can be significantly reduced. The effectiveness of the communicated content is not known until it is communicated and learned. To perform transfer learning, it is necessary to consider the relationship between the transfer destination and the transfer source, but even then, learning may not be successful and the transfer may not go well [3]. This study proposes several adaptive criteria indicators that can determine the validity of knowledge in advance.

A lot of research has been carried out to reduce learning time, and transfer learning is what makes this possible. Transfer learning is a method of adapting and reusing previously learned content from similar tasks to new tasks. Since there is no need to learn again, learning time can be shortened. The effectiveness of the transferred content is not known until it is transferred and learned, so when performing transfer learning, it is necessary to consider the relationship between the transfer destination and the transfer source. There is a possibility of failure [3]. This study proposed several new adaptive criteria indicators that can determine the validity of knowledge in advance.

2. Reinforcement learning

Reinforcement learning is a branch of machine learning in which an agent learns through interaction with its environment. Reinforcement learning is characterized by the fact that the agent chooses an action to achieve a certain goal and receives a reward signal for that action as it learns. Optimal behaviour rules are learnt by repeating steps 1 to 4 below.

1. Agent observes the state
2. Decides on a course of action based on cues from measures
3. Memorizes experience of which states, which actions and which rewards

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4. Seeks measures based on experience

Reinforcement learning is also formulated as a Markov decision process, expressed as M=(S,A,P,R) as follows.

- S: Set of states
- A: Set of actions
- P: State transition $p(s_t = s'|s_t = s, a_t = a)$
- R: Behaviour rules $\pi(s, a) = R(s_t = s, a_t = a)$

Reinforcement learning aims to acquire behaviour rules that maximize the expected reward.

2.1. *Q-learning*

In this study, Q-learning [3] was used as a reinforcement learning algorithm learning updates the Q-values that the agent associates with a combination of states and actions, and finds an action rule that selects the action with the maximum Q-value in each state. The formula for updating the Q-values is as follows.

$$Q(s_t, a_t) = Q(s_t, a_t) + \eta \\ * (R_{t+1} + \gamma \max Q(s_{t+1}, a) \\ - Q(s_t, a_t))$$

In this study, the ϵ-greedy method was also used as the agent's action selection method. In the ϵ-greedy method, the agent acts randomly with a probability of ϵ and selects an action with a probability of 1- ϵ with a maximum Q value.

3. Transfer learning

In transfer learning [4], [5], the goal is to reduce learning time by transferring knowledge learned at the transfer source as prior knowledge at the transfer destination with similar tasks. However, if there is no similarity between the source and destination, a negative transfer may occur. Therefore, the user must consider the similarity between the source and destination in advance. Therefore, it is necessary to determine the similarity between the source and destination to determine which knowledge is transferred to which destination.

In this study, we aim to formalize the adaptation criterion by determining the similarity between mazes using the maze problem.

3.1. *learning model*

The algorithm used for learning in reinforcement learning is Q-learning. There are five actions that the agent can take: up, down, left, right, left and right, and no action.

The reward design is +1 if the agent reaches the goal, and -0.01 if it collides with a wall or a step elapse.

3.2. *transition method*

As the transfer method uses Q-learning, the transfer learning adopts the value function transfer type. The Q-table obtained by the learning of the transfer source is transferred to the transfer destination agent. The degree of re-use of the behavioural value function is adjusted using the transfer rate τ. The transfer rate τ is adjusted in the range of $0 < \tau < 1$. In this study, τ was set at 0.5.

$$Q^c(s, a) = Q^t(s, a) + \tau Q^s(s, a)$$

4. Similarity Indicators

The following five indices are used to compute the similarity.

4.1. *Similarity by pixel value*

In this calculation example, the similarity by pixel value is determined. As the mazes used in this study have the same size, the percentage of pixel values matched between the images is determined.

4.2. *Cosine similarity between maze sequences*

In this example calculation, the maze is transformed into arrays and the cosine similarity between the source and destination arrays is calculated. The transformed array is the same as the array used for training, with the maze walls set to 1 and the paths set to 0.
- s is a vectorization of the base maze
- t is a vectorization of the destination maze.

$$cos(s, t) = \frac{\sum_i s_i t_i}{\sqrt{\sum_i s_i^2} \sqrt{\sum_i t_i^2}}$$

4.3. *Similarity using maxQ as weights*

In this calculation example, maxQ is used to determine the similarity. The total of the differences between the mazes is calculated using maxQ of maze A, which is the source of the transition, as the weight. The sum of the differences between the mazes is calculated using maxQ of maze A as the weight, and divided by the total value of maxQ.

$$p = 1 - \frac{\sum_i (s_i - t_i) \max_a Q_{s_i,a}}{\sum_i \max_a Q_{s_i,a}}$$

4.4. *Cosine similarity using maxQ*

Finally, in this calculation example, the Q values obtained after learning are used to obtain the cosine similarity. The Q values obtained after normal learning in each maze ($12 \times 12 \times 5$) are changed to an array of 12×12 by finding the maximum value (maxQ) in each square. However, this is not known before application as it is an outcome. It is calculated as part of the evaluation for measuring similarity.

$$\cos(\text{Max}_a Q_s, \text{Max}_a Q_t) = \frac{\sum_i \text{Max}_a Q_{s_i,a} \text{Max}_a Q_{t_i,a}}{\sqrt{\sum_i \text{Max}_a Q_{s_i,a}^2} \sqrt{\sum_i \text{Max}_a Q_{t_i,a}^2}}$$

5. Simulation

Five mazes were prepared to test the usefulness of the index. Maze A is the original maze and was applied to mazes B, C, D, and E, respectively. Fig. 1, Fig. 2, Fig. 3, Fig. 4, and Fig. 5 show the mazes.
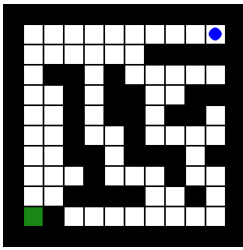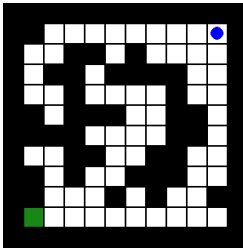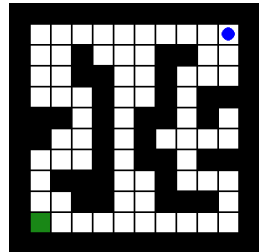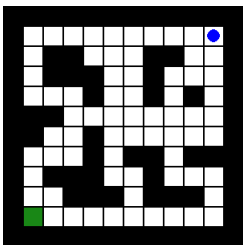

Fig. 1 Maze A
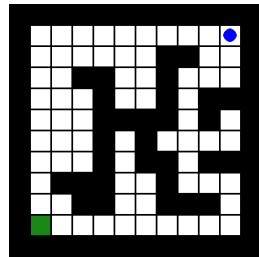
Fig. 2 Maze B

Fig. 3 Maze C

Fig. 4 Maze D

Fig. 5 Maze E

The similarity of the mazes to each indicator is shown in Table 1.

Table 1 Similarity Results

	Maze A to Maze B	Maze A to Maze C	Maze A to Maze D	Maze A to Maze E
Similarity by pixel value	82.95	77.08	80.02	79.44
Similarity between maze sequences	80.29	75.96	78.71	77.66
Similarity using Qmax	98.86	60.96	82.49	77.37
Cosine similarity using Qmax	72.97	5.89	41.17	28.91

S The Similarity results show that maze B, maze D, and maze C have the highest similarity in that order. Similarity by pixel value, similarity between maze sequences, and similarity using Qmax, in that order. The use of Q-values allows us to focus on differences only in important locations. Fig. 6, Fig. 7, and Fig. 8 show results of the transfer learning. Transition from maze A to maze C is not shown in the figure because the goal was not achieved. Reinforcement learning is represented by the red line and transfer learning by the blue line.
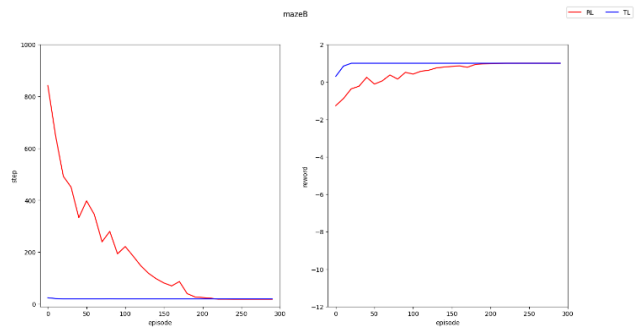

Fig. 6. Transfer learning from maze A to maze B, left panel shows number of steps to goal and episodes, right panel shows total reward and number of episodes.
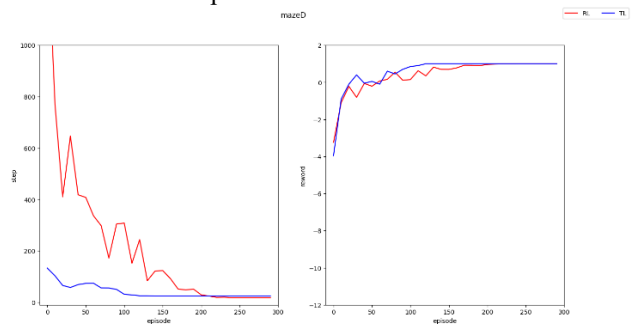

Fig. 7 Transfer learning from maze A to maze D, left panel shows number of steps to goal and episodes, right panel shows total reward and number of episodes
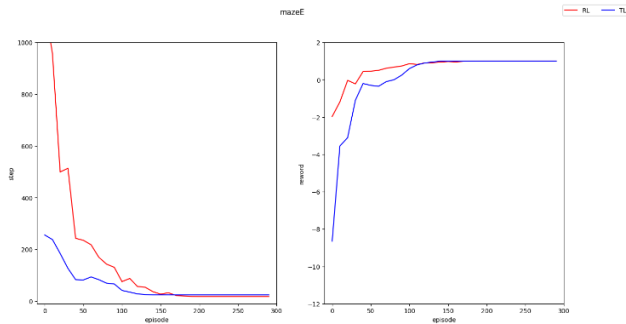
Fig. 8 Transfer learning from maze A to maze E, left panel shows number of steps to goal and episodes, right panel shows total reward and number of episodes

From these figures, the goal is reached faster with transfer learning than with reinforcement learning. This indicates that transition learning is effective in these mazes. Based on the results in the figures and the cosine similarity using Qmax, it seems reasonable to focus on the Q value.

Fig. 9 shows the results of applying reinforcement learning to the mazes. Fig. 10, Fig. 11, Fig. 12 and Fig. 13 show the results of applying transition learning to each maze. Red indicates locations with high rewards. The reward of maze A was applied to each maze. Therefore, the maze was routed from the top towards the goal. This demonstrates the validity of this simulation.
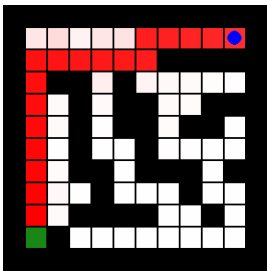

Fig. 9 Result of Reinforcement Learning on maze A
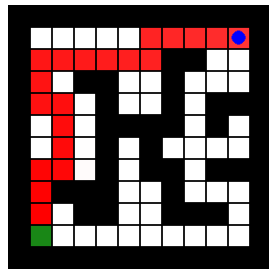

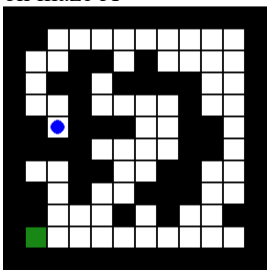Fig. 10 Result of Transfer learning on maze B

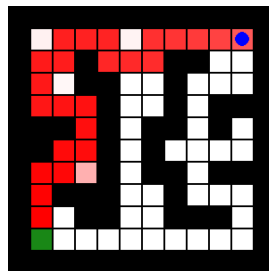Fig.11 Result of Transfer learning on maze C

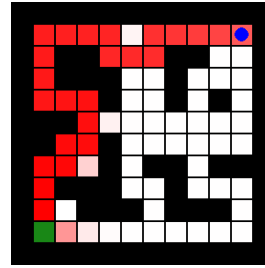
Fig.12 Result of Transfer learning on maze D

Fig.13 Result of Transfer learning on maze E

6. Conclusion

In this study, we conducted basic research on countermeasures for reinforcement learning that focused on environmental similarity. The simulation results confirmed the validity of focusing on maxQ and confirmed the validity of the index to some extent, allowing us to develop a new method. In the future, more accurate indicators will need to be created.

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