Feature Importance Evaluation Method
for Multi-Agent Deep Reinforcement Learning in Advanced Robotics Task Allocation

Sergey Ryabtsev
*Department of Computer Security, North-Caucasus Federal University, 1, Pushkin Street
Stavropol, 355017, Russia*

Mikhail Gurchinsky
*Department of Computer Security, North-Caucasus Federal University, 1, Pushkin Street
Stavropol, 355017, Russia*

Igor Struchkov
*Department of Organization and Technology of Information Security, North-Caucasus Federal University,
1, Pushkin Street, Stavropol, 355017, Russia*

Vyacheslav Petrenko
*Department of Organization and Technology of Information Security, North-Caucasus Federal University,
1, Pushkin Street, Stavropol, 355017, Russia*

Fariza Tebueva
*Department of Computer Security, North-Caucasus Federal University, 1, Pushkin Street
Stavropol, 355017, Russia*

Sergey Makarenko
*Laboratory of Information Technologies in System Analysis and Modeling, Saint Petersburg Federal Research Center
of the Russian Academy of Sciences, 39, 14 Line, Saint Petersburg, 199178, Russia
E-mail: nalfartorn@yandex.ru, gurcmikhail@yandex.ru, selentar@bk.ru, vipetrenko@ncfu.ru, ftebueva@ncfu.ru,
mak-serg@yandex.ru
www.ncfu.ru*

Abstract

The need to tackle intelligent tasks using advanced robotics multi-agent systems (MAS) actualize the use of artificial neural networks (ANNs) and multi-agent deep reinforcement learning technology. The article aims to solve the problem of exponential growth of ANN complexity with an increase in the number of agents in the MAS. To solve this problem, we propose an evaluation method for input data features importance. This method allows to optimize the input data feature set to reduce the computational complexity of the ANN inference while providing the same level of performance.

Keywords: Multi-agent systems, artificial neural networks, multi-agent deep reinforcement learning, feature importance

1. Introduction

The specific problems of learning ANN to control MAS agents have led to the emergence of such an area of machine learning as multi-agent deep reinforcement learning (MDRL)[1]. In contrast to single-agent deep reinforcement learning (SDRL), in the case of a MDRL, the ANN receives both features of the state of the environment and features of the state of other MAS agents:

$$F = \{X, F_1, \ldots, F_N\}, \qquad (1)$$

where F – set of features supplied to the input of the ANN; X – set of features of the state of the environment; F_i – set of features of the state of the i-th agent, $i = \overline{1, N}$; N – number of MAS agents. Thus, in the transition from SDRL to MDRL, a component of variable dimension $\{F_i | i = \overline{1, N}\}$ appears in the feature set F, which depends on the number of MAS agents N. To overcome this limitation, in work[2] in relation to the problem of tasks allocation[3], it was proposed to input the ANN with a set of features F', which includes the features of the state of not all agents, but only some of them:

$$F' = \{X, F_1, \ldots, F_{N'}\}, N' < N, F' \subset F, \qquad (2)$$

where N' – the number of agents whose features of the state are fed to the input of the ANN. This approach allows the use of MDRL for training MAS with a large number of agents, or MAS with a variable number of agents, for example, swarm robotic systems[4]. However, the problem of determining the optimal number of agents remains unsolved. To solve this problem, the in this article proposed a method for evaluation the importance of features in MDRL in problems of task allocation.

2. Related work

In work[5] proposed a combinatorial method for evaluation the importance of features based on combining features into subgroups, rearranging them, and retraining. The paper[6] raises the problem of combinatorial selection of the optimal composition of the used features. The authors proposed a method for evaluation the importance of features based on the use of the architecture of a double ANN – "operator" and "selector". The disadvantages of these methods are their high computational complexity. In work[7] proposed effective from the point of view of computational complexity, methods for evaluation the importance and choice of used features. However, these methods are focused on application in learning with a teacher.

The purpose of evaluation the importance of features in MDRL is to optimize their composition in order to achieve a compromise between computational complexity and the efficiency of MAS learning using some specific learning algorithm.

3. The proposed method for evaluation the importance of features

3.1. *Method description*

The proposed method based on the following hypothesis: in the case of a spatially distributed problem of task allocation features with low importance on average will make a small contribution to the value generated at the output of the ANN. Let us re-designate the grouped set of features F from Eq. (1) into an expanded set of features:

$$F = \{f_i | i = \overline{1, n}\}, \tag{3}$$

where n – the total number of features (environment and all agents).

Let us denote the MDRL process as a function l that returns some trained ANN π that approximates the behavior of MAS agents. The MDRL process is a function of the set of features F used:

$$l(F) \to \pi. \tag{4}$$

Let us also introduce the function $e(\pi)$ for evaluating the efficiency of the ANN π from the point of view of the purpose of the MAS:

$$e(\pi) \sim e. \tag{5}$$

The purpose of the estimates calculated using the proposed method is to determine such a subset of features $F' \subset F$, which can be excluded from the MDRL process l. In this case, an ANN π' should be obtained, the efficiency of which will be in a certain admissible neighborhood of the ANN efficiency π, trained on the full set of features F. Mathematically, this statement can be described as follows:

$$l(F \setminus F') \to \pi', \tag{6}$$

$$F \setminus F' = \{f_i \in F | f_i \notin F'\}, \tag{7}$$

$$|e(\pi') - e(\pi)| < \varepsilon, \tag{8}$$

where $F \setminus F'$ – the operation of subtracting the set F' from the set F, ε – given radius of the admissible neighborhood of the efficiency of the original ANN π.

To solve this problem the proposed method includes the following steps:

1. Training the ANN on the full set of features F using the training method l. As a result, ANN π is formed.

2. Calculation the estimate e of the efficiency of the ANN π.

3. Performing a test run of the ANN π at a certain number of steps. In this case, each state s_j supplied to the input of ANN π at the j-th step is recorded. As a result, a sample of data S is formed, supplied to the input of the ANN π:

$$S = \{s_j | j = \overline{1,m}\}, \tag{9}$$

where m – number of test run steps.

4. Further, for each feature $i = \overline{1,n}$, its elimination is emulated and the change in the ANN output π is evaluated based on the data of the test run S:

$$d_i = |\pi(S) - \pi(S \cdot M_i)|, i = \overline{1,n}, \tag{10}$$

$$M_i = \{m_j | j = \overline{1,n}\}, \tag{11}$$

$$m_j = \begin{cases} 0, \text{если } j = i, \\ 1, \text{если } j \neq i, \end{cases} \tag{12}$$

where M_i – the vector of masking of the i-th feature.

The obtained d_i values can then be used to evaluation the importance of the i-th feature.

Based on this method, the optimization of the set of used features F can be performed according to a scheme that includes the following steps.

1. The generated row d is processed by normalizing to the range $[0;\ 1]$ and ordering in descending order:

$$\bar{d} = \text{sort}\left\{\frac{d_i}{\max d_i - \min d_i} \middle| i = \overline{1,n}\right\}. \tag{13}$$

2. Some threshold value d_t is selected. If the value of the feature $\bar{d}_i$ is less than the threshold value d_t, this feature is included in the set of insignificant features F':

$$F' = \{f_i \in F | \bar{d}_i < d_t\}. \tag{14}$$

3. Based on the reduced set of features ($F \setminus F'$) the ANN π' is retrained and the efficiency is evaluation.

3.2. *Experimental results*

To test the efficiency of the proposed method, the simulated MAS was trained to solve the task allocation problem[2] using the modified MADDPG[2] method. The diagram of the series $\bar{d}$ obtained as a result of the application of the proposed method (Fig. 1). As follows from Fig. 1, starting with the features of the fourth agent's state, there is a sharp decrease in their importance.

To test the validity of this assumption, an optimization was carried out by brute force and training was carried out for a different number of agents (Fig. 2).

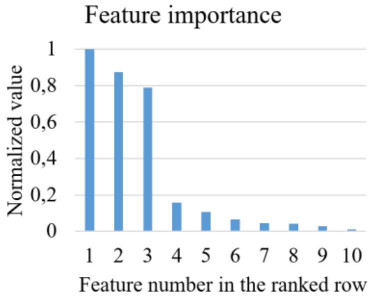


Fig. 1. Feature importance diagram.

As follows from Fig. 2 the effectiveness of functioning with a different number of agents more than two changes insignificantly. This confirms the adequacy of the results shown in Fig. 1. Similar efficiency is likely to be observed in other spatially distributed tasks, such as collective movement, or covering a certain area[8].

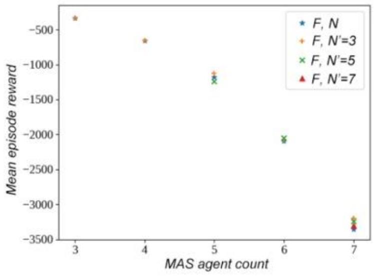


Fig. 2. Efficiency of trained ANN.

4. Conclusions

The article describes a proposed method for evaluation the importance of features. The essence of the proposed method is to evaluation the influence of the considered input feature on the change in the output signal generated at the ANN output. As follows from the results of experimental studies, the method can significantly reduce the number of used features without losing effectiveness. The advantage of the proposed method is its relatively low computational complexity.

References

1. P. Hernandez-Leal, B. Kartal, M.E. Taylor, "A survey and critique of multiagent deep reinforcement learning", Autonomous Agents and Multi-Agent Systems, Vol. 33(6), pp. 750-797, 2019.

2. V.I. Petrenko, F.B. Tebueva, A.S. Pavlov, M.M. Gurchinsky, "Multi-agent reinforcement learning method in systems with a variable number of agents", Information Technologies for Intelligent Decision-Making Support (ITIDS), 2021.
3. H. Hamann, "Swarm Robotics: A Formal Approach", Springer, Cham, 2018.
4. A. Zakiev, T. Tsoy, E. Magid, "Swarm Robotics: Remarks on Terminology and Classification", Lecture Notes in Computer Science, Vol. 11097, pp. 291-300, 2018.
5. C. Molnar, G. König, B, Bischl, G. Casalicchio, "Model-agnostic Feature Importance and Effects with Dependent Features - A Conditional Subgroup Approach", arXiv, 2021.
6. M. Wojtas, K. Chen, "Feature Importance Ranking for Deep Learning", arXiv, 2020.
7. G. Wei, J. Zhao, Y. Feng, A. He, J. Yu, "A novel hybrid feature selection method based on dynamic feature importance", Applied Soft Computing, Vol. 93(6):106337, 2020.
8. Y. Wang, M. Svinin, E. Magid, R. Sun, Y. Bai, "Adaptive Multi-Agent Coverage Control With Obstacle Avoidance", IEEE Control Systems Letters, Vol. 6, pp. 944-949, 2022.

Authors Introduction

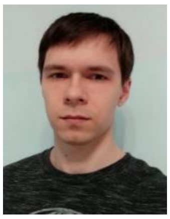
Mr. Sergey Ryabtsev

He received his Specialist's degree from the Department of Computer Security, North-Caucasus Federal University, Russia in 2016. He is currently a Master student in North-Caucasus Federal University, Russia.

Mr. Mikhail Gurchinsky

He received his Master's degree from the Department of Information Systems and Technologies, North-Caucasus Federal University, Russia in 2016. He is currently a postgraduate student in North-Caucasus Federal University, Russia.

Mr. Igor Struchkov



He received his Specialist's degree from the Department of Computer Security, North-Caucasus Federal University, Russia in 2019. He is currently a postgraduate student in North-Caucasus Federal University, Russia.

Mr. Vyacheslav Petrenko

He is Head of the Department of Organization and Technology of Information Security, North-Caucasus Federal University in Russia. He received his Ph.D. degree in Military control, communications and navigation systems in 1994. His research interests are Artificial intelligence.

Ms. Fariza Tebueva

She is Head of the Department of Computer Security, North-Caucasus Federal University in Russia. She received her Doctor of Physics and Mathematical Sciences degree in Mathematical modeling, numerical methods and program complexes in 2014. Her research interest is Swarm Robotics.

Mr. Sergey Makarenko

He is a Professor of Department of Information Security, Saint Petersburg Electrotechnical University "LETI" in Russia. He received his Doctor of Engineering Sciences degree in Systems, networks and telecommunication devices in 2018. His research interest is telecommunication networks.