Weakness Analysis of Cyberspace Configuration Based on Reinforcement Learning

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Abstract
In this work, we present a learning-based approach to analyze cyberspace configuration. Unlike prior methods, our approach has the ability to learn from past experience and improve over time. In particular, as we train over a greater number of agents as attackers, our method becomes better at rapidly finding attack paths for previously hidden paths, especially in multiple domain cyberspace. To achieve these results, we pose finding attack paths as a Reinforcement Learning (RL) problem and train an agent to find multiple domain attack paths. To enable our RL policy to find more hidden attack paths, we ground representation introduction and multiple domain action select module in RL. By designing a simulated cyberspace experimental environment to verify our method. Our objective is to find more hidden attack paths, to analysis the weakness of cyberspace configuration. The experimental results show that our method can find more hidden multiple domain attack paths than existing baselines methods.

1. Introduction
Rapid progress in AI has been enabled by remarkable advances in computer systems and hardware, but it is not widely used in cyberspace security protection. However, the intellectualization of cyberspace security protection system is an important problem facing the current cyberspace security protection(Rajkumar et al., 2010). In the security management of cyberspace, actually the cyberspace should be regarded as a space composed of physical domain, digital domain and social domain, and its security protection should also be conducted as a whole(Lee et al., 2016). In this process, it mainly includes the configuration of intelligence discovery of weakness, intelligent deployment of security equipment(Heo and Varshney, 2005), intelligent monitoring of network traffic, intelligent awareness of security situation and other parts(Yao et al., 2019), which comprehensively constitute the cyberspace security protection system. We believe that it is AI itself that will provide the means to constitute the cyberspace security protection system, creating a symbiotic relationship between cyberspace security and AI with each fueling advances in the other.

In this work, we present a learning-based approach to analysis cyberspace configuration. Our objective is to find more hidden attack paths, to analysis the weakness of cyberspace configuration. Despite of research on this problem, it is still necessary for human experts to realize the security risks existing in the current cyberspace of accurate judgment and evaluation, in order to ensure the security of the entire cyberspace. The problems complexity arises from multiple domain interaction each other in cyberspace, and only digital domain or network domain can be considered in current research. Even after breaking the problem into more manageable sub-problems, the state space is still orders of magnitude larger than recent problems on which intelligent-based methods have shown success.

To address this challenge, we pose find multiple domain attack paths as a Reinforcement Learning (RL) problem, where we train an agent (as an attacker) to find the attack paths. In each iteration of training, all of the attack paths are sequentially found by the RL agent. Training is guided by a fast but approximate reward signal for each of the agents find attack paths.

To our knowledge, in order to realize the target, the following problems need to be solved:

- First, the problem of multiple domain which can inter-
action each other. This paper studies the problem of multiple domain cyberspace, and changes the existing cyberspace security risk analysis to focus on multiple domain cyberspace, enforce the pertinence and relevance of business level.

- Second, the problem of the alternative actions in different states is different. In traditional RL, the number of actions which agent can select is the same in any state. Therefore, this paper introduction the multi-domain action select module in RL algorithm, in order to make the alternative actions in different states is different.

- Third, the problem is how to measure the cyberspace weakness by multiple domain cyberspace attack paths. This paper proposed an basic index measured by the average attack paths of all attackers in the cyberspace. In this way, we can measure the weakness of different cyberspace configuration, thus provides the correlation reference for the different cyberspace configuration, to help the administrator to improve the cyberspace security.

We believe that the ability of our approach to learn from experience and improve over time unlocks new possibilities for network administrator. We show that we can achieve superior result on simulated cyberspace experimental environment, as compared to the baselines method. Furthermore, our methods can find more hidden attack paths comparable to human expert based method in same time. Although we evaluate primarily on cyberspace configuration analysis, our proposed method is broadly applicable to many cyberspace security analysis.

2. Related Work

2.1. Intelligent Security Protection

Intelligent security protection mainly studied the behavior characteristics and rules of users network monitoring and network optimization. In general, there is an attack in the cyberspace, when it appears, the traffic will change, we can take advantage of the attack mode type to detect cyberspace anomalies. Collect the original message of the data in the network and extract it. Take the destination address and other information, establish the normal traffic model, and then use discrete wavelet transform technology analyzes and detects the data flow to judge the cyberspace anomalies(Kim and Reddy, 2008).

At present, the intelligent security protection technology based on cyberspace user’s action mainly relies on web data mining, user abnormal action detection and neural network based method to distinguish. Combining traditional data mining techniques with the Internet for web mining is to extract potentially useful patterns and hidden information from web documents, web structures and service logs. Generally, according to the different objects of web mining, people divide web data mining into three types: web content mining, web structures mining, use record mining and web comprehensive mining(Badea et al., 2015).

In the operation process of users will retain a lot of action information, effective use of this information is the basis and key to the realization of abnormal action determination. Multi-layer log collection is implemented to support the decision of user access action. Using multi-level user access log, and integrate web front end user click action and URL access logic, to extract the user’s access action characteristics, by a large number of calculating the average user action baseline characteristics, use of effective monitoring abnormal access action scoring algorithm, trace the action of the abnormal IP, corresponding treatment measures(Beutel et al., 2015).

As an important method to deal with nonlinear systems, the neural network method has been successfully applied in the fields of pattern recognition and probability density estimation. Compared with the statistical analysis theory, the abnormal behavior analysis method based on neural network can better express the nonlinear relationship between one variable and another. The changing of abnormal network action requires the ability of behavior analysis system to analyze a large number of network packets. Moreover, many common attacks may be coordinated by multiple attackers on the cyberspace, which requires the network abnormal action analysis system must have the ability to deal with a large amount of nonlinear data. The method based on neural network has a fast response ability, especially for the processing of noisy data and incomplete data, so it provides a great flexibility for the analysis of intelligent security protection(Kawazu et al., 2016).

In recent years, the emergence of machine learning has made intelligent security protection become a new trend. There are many new attempts, including SVM(Liao et al., 2013)(Gao et al., 2017), K-nearest neighbors(Xu et al., 2017), Naive Bayes(B and Muneeswaran, 2019), random forests(Zhang et al., 2008), neural network(Akashdeep et al., 2017), deep learning and so on. The methods based on deep learning have become mainstream in the field because of their better performance. Gao proposed an model based on deep belief network, which uses a multi-layer unsupervised learning network and a supervisor-based backpropagation network(Qu et al., 2017). Shone used asymmetric depth self-encoders to learn network traffic characteristics in an unsupervised, not only achieved good performance on large data sets, but also reducing training
time (Shone et al., 2018). Yin proposed a model using RNN, compared the effectiveness of the non-depth model, and achieved good performance (Yin et al., 2017). Kim proposed a model using LSTM and gradient descent strategy. The experiment result which proved the LSTM can achieve a better performance (Le et al., 2017). Sheraz conducted a comprehensive study on deep learning model, and proved that the deep learning method can not only be used in this field, but also can achieve better performance (Naseer et al., 2018).

2.2. Reinforcement Learning

Reinforcement learning is commonly considered as a general machine learning model, it mainly studies how agent can learn certain strategies by interacting with the environment, to maximize long-term reward. RL is based on the Markov Decision Process (MDP) (Sutton and Barto, 1998). A MDP is a tuple \((S, A, T, R, \gamma)\), where \(S\) is the set of states and \(A\) is the set of actions. \(T(s_i | s_j, a): T \times A \rightarrow R\) is the reward after executing action \(a\) at stage \(s_i\), and \(\gamma\) is the discounting factor. We used \(\pi\) to denote a stochastic policy, \(\pi(s, a): T \times A \rightarrow [0, 1]\) is the probability of executing action \(a\) at state \(s\) and \(\sum_{a \in A} \pi(s, a) = 1\) for any \(s\). The goal of RL is to find a policy \(\pi\) that maximizes the expected long-term reward. Besides, the stateaction value function is

\[
Q^\pi(s, a) = E \left[ \sum_{t=0}^{\infty} \gamma^t R(s_t, a_t) | s_0 = s, a_t \sim \pi(s_t) \right]
\]

which \(\gamma \in (0, 1]\) measure the importance of future reward to current decisions.

For different policies \(\pi\), they represent the possibility of different actions selected in the same state, and also correspond to different rewards. A better policy can select better action in the same state, to obtain more reward.

In traditional RL, the action-value function is calculated interactively, and will eventually converge and obtain the optimal strategy, mainly including Dynamic Programming, Monte Carlo Method and Temporal-Difference Learning. After deep learning was proposed, the deep reinforcement learning method formed by combining RL is the mainstream method at present.

In the following, we introduce the mainstream RL algorithm DDPG.

Deep Deterministic Policy Gradient (DDPG):

DDPG (Lillicrap et al., 2015) is a learning method that integrates deep learning neural network into Deterministic Policy Gradient (DPG) (Silver et al., 2014). Compared with DPG, the improvement the use of neural network as a policy network and \(Q\)-network, then used deep learning to train the above neural network. DDPG has four networks: actor current network, actor target network, critic current network and critic target network. In addition to the four network, DDPG also uses experience playback, which is used to calculate the target \(Q\)-value. In DQN, we are copying the parameters of the current \(Q\)-network directly to the target \(Q\)-network, that is \(\theta_Q^T = \theta_Q\), but DDPG use the following update:

\[
\begin{align*}
\theta_Q^T &\leftarrow \tau \theta_Q + (1 - \tau) \theta_Q^T \\
\theta^T &\leftarrow \tau \theta^T + (1 - \tau) \theta^T
\end{align*}
\]

where \(\tau\) is the update coefficient, which is usually set as a small value, such as 0.1 or 0.01. And this is the loss function:

\[
L(w) = \frac{1}{m} \sum_{j=1}^{m} (y_j - Q(\phi(S_j), A_j, w))^2
\]

3. Methods

The influence of cyberspace security is mainly reflected in different cyberspace configurations, which can influence the length or concealment of attack paths in cyberspace. Different configurations in cyberspace can change attacker’s attack paths in different ways. It is generally believed that cyberspace contains physical domain, digital domain, cognitive domain, social domain, etc. Since the relationship between people and people in the social domain generally changes in real time, it is not considered for the time being. In this paper, the relevant configuration and related authority of physical domain, digital domain and cognitive domain are mainly considered.

After analyzing the relation between cyberspace authority, namely can analysis the cyberspace configuration weakness, its basic idea is if an attacker can find attack paths under current cyberspace configuration. If under a certain cyberspace configuration, the attacker can more easily find attack paths, as a result, the attacker can easily modify the cyberspace configuration and obtain the security information, illustrates the cyberspace configuration is bad. On the other hand, the security of cyberspace configuration is necessary. So we proposed the method to analysis the weakness of cyberspace, to find the attack paths to analysis weakness in the current cyberspace, then enhance the cyberspace security based the weakness analysis result.

3.1. The Weakness Analysis Architecture

The input of cyberspace configuration weakness analysis architecture is the current cyberspace configuration, through the malicious action analysis model to analysis its possible malicious actions, get the attacker’s attack
paths, ultimately rely on the cyberspace multiple domain attack paths, according to the cyberspace configuration index value, calculate the weakness of the current cyberspace configuration. The architecture is shown in Figure 1.

This process is divided into two core processes, first is through the current cyberspace configuration, we will get the corresponding cyberspace attack paths based on the malicious action analysis model, this is the most critical in this process. In this process, we use the DDPG algorithm, and represent an attacker as an agent. The agent can learning cyberspace intrusion policy by its autonomous, and then find the attack paths in cyberspace, therefore the agent can find the hidden attack paths. Second is calculating the cyberspace configuration’s weakness, mainly through compute cyberspace attack paths to calculate cyberspace configuration weakness value. In the process, because of the different attackers’ initial permissions, the cyberspace attack paths is different, so we need to comprehensive analysis of different attackers, integrated to the cyberspace attack path of different initial permission attackers, and corresponding the weakness of cyberspace configuration is obtained.

3.2. Malicious Action Analysis Model

The main function of the malicious action analysis model is to obtain the possible cyberspace attack paths of an attacker who given its initial permission under a certain cyberspace configuration. In this process, we use DDPG algorithm, and the attacker with initial permissions are represented as the agent, who can learn cyberspace intrusion strategy autonomously and obtain cyberspace attack paths.

Specifically, the malicious action analysis model takes DDPG algorithm, we are using an agent to represent the likely attacker. In the process of finding the attack paths, the agent first selects the action in the current state, which can change the environment (cyberspace configuration) and the agent’s state. At the same time the agent will obtain certain reward, negative reward (captured by administrator) or none. Besides, the change in the agent’s state enables it to perform other actions to obtain more rewards. As a result, the agent finds attack paths in this cyberspace configuration by trial and error. The model is shown in Figure 2.

The goal of malicious action analysis model is to find an optimal policy given a cyberspace state, and to select the corresponding action $a$ according to the current state $s$ of the cyberspace, it also means find the corresponding policy mapping function $R(s) \rightarrow A$, to make the long-term reward of agent maximum. In this process, the policy can be divided into two categories, namely the deterministic policy and the stochastic policy, deterministic policy is for the state, the conviction of corresponding output (action). In general, the deterministic policy algorithm efficiency is high, but the lack of ability to explore and improve. Rather than the stochastic policy is based on deterministic policy, to join corresponding random value, enables the stochastic policy to have certain ability of exploration. For the malicious action analysis model, since the action value range is generally not large in practical problems, a deterministic policy is adopted to ensure better performance of the model.

The malicious action analysis model treats the problem as a MDP, that is $M = (S, A, P, R, \gamma)$, where is $s \in S$ the current state of the cyberspace, $a \in A$ is an attack action that is currently available, $P$ is the probability of transitions between states, $R$ is the reward value after taking an action to reach the next state. $\gamma$ is the discount factor. For the transfer probability, it can be expressed formally as $p(\hat{s}|s, a) = p(S_{t+1} = \hat{s}|S_t = s, A_t = a)$. For the reward function, it can be formally expressed as $R(s, a) = E[R_{t+1}|s, a]$.

On the specifically model, the malicious action analysis model is a standard RL model, through the study of the awareness of environment, the agent will take the action and get a reward, the goal of the agent is to maximize rewards, and then to further training of the agent. In this
paper, we will take DDPG algorithm, and its main architecture as shown in Figure 3.

With the standard DDPG algorithm, the basic architecture of the malicious action analysis model also consists of four networks and one experience replay memory. Among them, the experience replay memory is mainly responsible for storing the state transfer process of \(<s, a, r, s'>\). Then, by means of small batch sampling, the corresponding transferred samples are extracted to train the corresponding neural network so as to avoid the strong correlation between samples. Among the four networks, there are two policy networks (Actor) and two Q-networks (Critic), namely the online policy network, the target policy network, the online Q-network, and the target Q-network. The policy network mainly simulates the attacker’s policy through the deep neural network, which takes the current state as the input and the output as the corresponding action. The Q-network is mainly used to estimate the expectation of the final reward value obtained if the policy is continuously executed after the current action is executed in a certain state. The input is the current state, the current action and the output is the Q-value. If only a single neural network is used to simulate policy or Q-value, the learning process is unstable. So in DDPG algorithm respectively, policy network and Q-value network create copies of two networks, two networks are known as the online network, two networks are known as the target network, online network is the current training of network, the target network is used to calculate the training goal, and after a short period of time, the model of online networks parameter updates to the target networks, so as to make the training process is stable, easy to convergence.

We have improved the standard DDPG algorithm, which is different from the standard DDPG algorithm in three aspects:

- In improved DDPG algorithm, we introduced the multi-domain action selection module.

  Different from standard DDPG algorithm, the biggest change is that the introduction of multi-domain action selection module. In the standard DDPG, the actions which agent can choose in each state is the same. But in this environment, when the attacker select the attack paths in cyberspace, he have different alternative actions in each state. In order to make DDPG algorithm can choose different actions in different states, joined the multi-domain action selection module. This module’s input is online policy network’s output, theory action \(a_t\), then a linear change under this current state, and perform the actual action \(a'_t\), the actual execution action \(a''_t\) into multi-domain action execution module, get the corresponding reward \(r'_t\). In the end, the corresponding actual execution of action \(a''_t\) and the corresponding reward \(r'_t\) return online policy network. Through this method, the reasonable choice of actions in different states can be realized.

- Second, the input of experience playback memory is different.

In order to ensure that the multi-domain action selec-
tion conforms to the constraints of the actions on the state, the input of the experience playback memory is increased, not only by the online policy network to store the sequence \((s_t, a_t, r_t, s_{t+1})\), that is, execute the action \(a_t\) in the state \(s_t\), get the reward value \(r_t\), and convert the relevant state to \(s_{t+1}\). Moreover, since the corresponding relationship between the state and the action needs to be considered when selecting the action, it is avoided that the policy network chooses the action that is not feasible in the state. Therefore, when the policy network selects an inoperable action \(a_t\) in the state \(s_t\), it is not only necessary for the multi-domain action selection module to use a linear transformation to map it to a feasible action \(a'_t\). In addition, relevant action sequences \((s_t, a_t, -\infty, s_{t+1})\) need to be taken to indicate that actions \(a_t\) are executed in the state \(s_t\), and the subsequent state obtained is still \(s_t\), and the reward at this time is a huge negative value, so as to ensure that relevant actions are not selected in the process of training the policy network.

- At last, the architecture of the policy network is changed based on the relevance of the input state.

In terms of network architecture, the two policy networks have the same architecture, whose input is the state of network and output is the action to be selected. Structurally, a RNN hidden node is added between the original DDPG input layer and the hidden layer. The transformed policy network is divided into 5 layers. The first layer is the input layer; The second layer is the RNN hidden layer, which contains 32 GRU nodes. Layer 3th and layer 4th are the full connected layer, including 48 full connected nodes. The activation function uses the ReLu function. The fifth layer is the output layer, use the sigmoid function as the activation function, and finally output a multi-dimensional vector representing the multi-domain action that needs to be performed.

In addition, the two \(Q\)-networks have another architecture, whose input is not only the state of the network, but also includes a multidimensional vector, representing the corresponding multi-domain actions, and the output is a scalar, representing the corresponding \(Q\)-value of the corresponding states and actions. The network is divided into four layers. The first layer is the input layer; The second layer and the third layer respectively contain 48 fully connected nodes. The activation function uses the ReLu function. The fourth layer is the output layer, which outputs a scalar and uses the linear function as the activation function, representing the corresponding \(Q\)-value of the corresponding state and action.

### 3.3. Cyberspace Configuration Weakness Metrics

The measurement of cyberspace configuration weakness is the basic index measured by the average attack path of all users in the cyberspace, as shown in equation 4:

\[
sec(s) = \lim_{n \to \infty} \frac{\sum_{i=1}^{n} \text{len}(A(u_i))}{n}
\]

Among them, \(s\) is the multiple domain configuration of the current cyberspace, which is the object to be evaluated; \(sec(s)\) is the security measures configured for the current multiple domain cyberspace; \(n\) is the number of attackers. For the same attackers with different initial states, they can be considered as different network attackers, \(u_i\) is the user \(i\), \(A(u_i)\) is the shortest attack path of the user \(i\). \(\text{len}(path)\) is the length of the path \path. The attack path is the attacker how he can get the security information from the initial permission through the relevant steps.

By the equation 4 can be seen that for measurement cyberspace configuration weakness, can be turned into search for the most likely attack paths, by this measure, the cyberspace configuration weakness metric into intelligence agent to autonomous learning, to enhance the automation of the cyberspace security configuration has the profound significance.

### 4. Experiments

#### 4.1. Experiment Environment

In the experiment, the corresponding simulation environment is constructed to verify the effectiveness of the method. In this environment, there are five spaces in total. The outermost space is the whole physical space, representing a region. P1 is the region where terminal located, P2 is the region where VPN equipment located, P3 is the location of the communication team, and P4 is the communication hub. There are 5 kinds of equipment, including computer 2 sets (T1 and T2, respectively stored in P1 and P3), firewall 2 sets (FW1, FW2, respectively stored in P3 and P4), sensor (D1, stored in P2), router (R, stored in P4) and switch (SW, stored in P4), server 2 sets (S1, S2, stored in P4) and its equipment connection relationship as shown in Figure 4. The security information is stored in S2.

In this network, there are 15 network services, as shown in Table 1.

In this environment, because of the firewall FW1 equipment are in need of remote management, FW1-password remains in FW1, at the same time, due to the T2 maintains FW2 and S1, so T2 store password FW2.password and S1_web_password, in this environment, to ban other flow.
of information. But we can know, an attacker can through the multiple domain joint attack, which can obtain the security information stored on the server S2, a possible attack path is as follows:

First, attacker enter space P2 and obtain the management service password FW1_password of firewall FW1;

Second, use device T1 or D1 to access the management service of FW1, add access control list: allow T1 or D1 to access the management service of T2, that is T2_manager;

Third, get the password FW2_password of firewall FW2 stored on T2 and the password S1_web_password of service S1_web through T2_manager;

Fourth, use T2_S1 port, access firewall FW2_manager, add access control list: allow T1 or D1 access service S1_web and S2_web;

Fifth, use T1 or D1 to access the service S1_web and get the password S2_web_password of S2_web, at this point, the attacker’s higher permissions have been obtained.

At last, the attacker can use T1 or D1 to access the service S2_web to get the security information by the S2_web_password.

In this process, three key firewall security policy changes are involved: on firewall FW1, T1 or D1 are allowed to access T2’s management service T2_manager; On firewall FW2, allow T1 or D1 to access service S1_web; On firewall FW2, allow T1 or D1 access to the service S2_web.

4.2. Experiment Process

During the experiment, an agent(attacker) is introduced, located in the outermost space, and then, in the environment shown in Figure 4, for three key security policies (on firewall FW1, T1 or D1 are allowed to access T2’s management service T2_manager; On firewall FW2, allow T1 or D1 to access service S1_web; On firewall FW2, allow T1 or D1 to access the service S2_web). Randomly add 0 or more security policies, and respectively calculate the average attack action length of the attacker to obtain security information when the number of key security policies is different (if the attack action length exceeds 10000, it will be forced to quit, which means that the attack is unsuccessful, otherwise, the action sequence length of the first time to obtain the security information will be recorded).

According to the malicious action analysis model, according to the DDPG algorithm, define the corresponding state, action, reward, etc. The relevant settings are as follows:

On the set of state, with a length of 106 vector to represent a state of different position on the value of the vector may users, respectively from the spaces, the ports, services or information, in setting a state vector, if in the state, the attacker exists, will be to the attacker’s value is set to 1, otherwise 0. If the attacker is in a certain space, the value representing that space is set to 1; otherwise, it is 0. If the attacker uses a port, set the value representing the port to 1, otherwise 0; If the attacker is connected to a service, set the value representing the service to 1, otherwise 0; If the attacker obtain security information, set the value representing that information to 1, otherwise 0.

Attackers have different action in different states. For example, when the attacker can dominate the management service FW1_manager of FW1 in the current state, he can add the corresponding access control list for firewall FW1 in the current state. Otherwise, he cannot add the access control list for FW1. For example, if the attacker is able to access the service S1_web in the current state and has the password S1_web_password, he can dominate the service. If it has access to the service S1_web, but does not have the password S1_web_password, he cannot dominate the service.
In terms of the reward setting, different rewards are set for the attacker according to the degree of the completion of the attack path. Among them, when the attacker can dominate the management service `FW1_manage` of FW1, its current reward is 100. When the attacker can dominate the management service `FW2_manage` of F2, its current state reward is 200. When the attacker obtains the administrative service password `S1_web_password` of the `S1_web`, the reward is set to 300. When the attacker obtains the administrative service password `S2_web_password` of `S2_web`, the reward is set to 400. When the attacker obtains the final security message, the reward is set to 10000.

4.3. Results and Discussions

Under the above conditions, learn 60 times in different environments respectively, and calculate the corresponding attack sequence length. First of all, the attacks on a policy for statistical learning process, the process of two typical as shown in Figure 5, with the increasing the number of training, the reward present a slow upward trend, until finally tend to be convergent, it is in a learning process of RL, shows that the proposed model can monitor to the attacker’s action of gradually learning the characteristics of an attacker’s action rule, and constantly improve its accuracy of judgment, so as to verify the effectiveness of the proposed model is presented in this paper.

Secondly, the length of the attack path under different security configurations is calculated. According to the number of policies added, the length of the possible attack path is calculated, as shown in Figure 6.

From Figure 6, adding in the key security policies, the more attacks the attackers more easily to the anticipated target, this also from the side the important of the configure security. Besides, the length of the attacker’s attack path in this configuration is used to measure the weakness of cyberspace, it also shows that the level of cyberspace configuration security can affect the attacker attack difficulty, this verified the correctness of the proposed method.

5. Conclusion

Based on the current cyberspace configuration lack of multiple domains attack evaluation, we proposed the weakness analysis of cyberspace configuration based on reinforcement learning. Meanwhile, we has been learn about the cyberspace weakness metrics, and finally has carried on the experimental verification. This method can comprehensively consider the mutual influence of the multiple domain configuration in the cyberspace, and can take an intelligent method to analysis the weakness of the cyberspace, which has a strong practical value.

This paper analysis a typical cyberspace environment and applies the reinforcement learning method to analysis of cyberspace configuration, which has achieved better results. However, the cyberspace environment in this paper is limited. In the next step, we hope to apply the reinforcement learning to more cyberspace operation and maintenance management, and achieve better results.
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