

Predictive Optimization of DDoS Attack Mitigation in Distributed Systems using Machine Learning

Baoming Wang^{1*}

Electrical and Computer Engineering, University of Illinois Urbana-Champaign, Urbana, IL, USA

*Corresponding author: wangbm0215@gmail.com

Yuhang He¹

Computer Science and Technology, Tianjin University of Technology, Tianjin, China

deushawakami@gmail.com

Zuwei Shui²

Information Studies, Trine University, Phoenix, USA

tuilzhizimoon@icloud.com

Qi Xin³

Management Information Systems, University of Pittsburgh, Pittsburgh, PA, USA

QIX29@pitt.edu

Han Lei⁴

Computer Science Engineering, Santa Clara University, Santa Clara, USA

hannahleigh19970807@gmail.com

Abstract

In recent years, cloud computing has been widely used. Cloud computing refers to the centralized computing resources, users through the access to the centralized resources to complete the calculation, the cloud computing center will return the results of the program processing to the user. Cloud computing is not only for individual users, but also for enterprise users. By purchasing a cloud server, users do not have to buy a large number of computers, saving computing costs. According to a report by China Economic News Network, the scale of cloud computing in China has reached 209.1 billion yuan. At present, the more mature cloud service providers in China are Ali Cloud, Baidu Cloud, Huawei Cloud and so on. Therefore, this paper proposes an innovative approach to solve complex problems in cloud computing resource scheduling and management using machine learning optimization techniques. Through in-depth study of challenges such as low resource utilization and unbalanced load in the cloud environment, this study proposes a comprehensive solution, including optimization methods such as deep learning and genetic algorithm, to improve system performance and efficiency, and thus bring new breakthroughs and progress in the field of cloud computing resource management. Rational allocation of resources plays a crucial role in cloud computing. In the resource allocation of cloud computing, the cloud computing center has limited cloud resources, and users arrive in sequence. Each user requests the cloud computing center to use a certain number of cloud resources at a specific time.

key words :

Cloud computing; Resource scheduling; Machine learning optimization; Artificial intelligence

1 INTRODUCTION

In today's digital age, the web has become central to our daily lives and business activities. However, this has been followed by a proliferation of cybersecurity threats, of which distributed denial of service (DDoS) attacks are undoubtedly one of the most destructive forms. This article will delve into the various aspects of DDoS attacks and the basic principles, types, examples, and effective defense strategies of DDoS implementation in distributed systems combined with artificial intelligence.

Looking ahead to 2024, Gcore has released its latest [1]DDoS attack trends report for the third and fourth quarters of 2023 (Q3-Q4), highlighting an alarming increase in both the size and complexity of DDoS attacks. Gcore found that peak DDoS attack traffic has increased by more than 100% in each of the last three years, with peak DDoS attack traffic of 300Gbps in 2021, rising to 650Gbps in 2022 and increasing again to 800Gbps in Q1-Q2 2023. Rising to 1600 Gbps (1.6 Tbps) in Q3-Q4 2023.

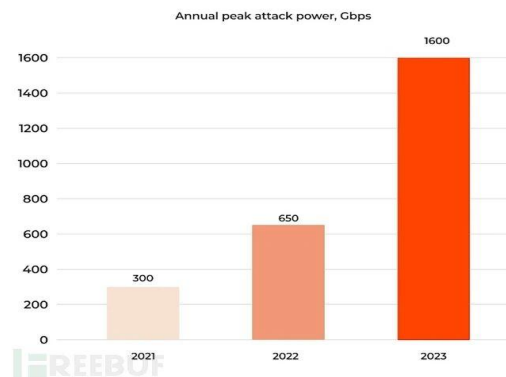


Figure 1.DDoS attack application growth trend

Of these, the jump in the second half of 2023 means that the cybersecurity industry is measuring DDoS attacks in a new unit, terabits (TB). This indicates that the potential damage from DDoS attacks is escalating significantly and continuously, and Gcore expects this trend to continue through 2024.

DDoS attacks operate on a fundamental principle: overwhelming the resources of a target system, service, or network to disrupt its ability to respond to legitimate user requests. [2]This nefarious tactic relies on orchestrating a large number of compromised computers or devices into a vast "botnet." With this powerful network at their disposal, attackers collaborate to launch massive assaults on their targets, inundating them with an avalanche of traffic. Conceptually, a DDoS attack can be likened to a cyber traffic jam, where attackers flood the virtual lanes with fake requests, effectively blocking access for legitimate users. The ramifications extend beyond mere inconvenience; DDoS attacks pose serious threats, compromising service availability, causing business disruptions, exposing sensitive data, and inflicting financial losses.

Distributed Denial-of-Service (DDoS) attacks pose a significant threat to the stability and security of online services, networks, and systems. These attacks operate on a simple yet devastating principle: overwhelming the resources of a target, rendering it incapable of responding to legitimate user requests. In essence, DDoS attacks create a cyber traffic jam, blocking access for genuine users and causing disruptions that can lead to severe consequences such as business downtime, data breaches, and financial losses.

To address this pressing issue, the integration of machine learning techniques offers a promising approach: predictive optimization. By leveraging the power of machine learning algorithms, predictive optimization aims to anticipate and mitigate DDoS attacks before they occur. This proactive strategy involves analyzing large volumes of data to identify

patterns and anomalies indicative of impending attacks. Through this process, machine learning models can learn from past attack instances and predict future threats with a high degree of accuracy.

In this context, predictive optimization using machine learning serves as a proactive defense mechanism against DDoS attacks. By anticipating and preemptively mitigating threats, organizations can enhance the resilience and robustness of their online services and networks. This introduction sets the stage for exploring the methodology, implementation, and potential benefits of leveraging machine learning for predictive optimization in DDoS attack mitigation.

2 RELATED WORK

2.1 Previous Studies on DDoS Attack Mitigation

In recent years, with the rapid development of the Internet, DDoS (distributed denial of Service) attacks have posed a serious threat to network security. To address this challenge, researchers are constantly exploring new methods and techniques to protect against DDoS attacks. The following is an overview of the research progress of DDoS attack prevention based on actual data:

Enhanced real-time monitoring and analysis : [3]Research shows that real-time monitoring of network traffic and timely analysis of anomalies is the key to effectively preventing DDoS attacks.Ke Yichuan and other researchers deeply discussed the key role of TCP/IP protocol in network communication, and focused on the analysis of DoS and DDoS attacks. By analyzing the attack mode, he puts forward some preventive measures, such as network traffic monitoring, intrusion detection system deployment and network traffic filtering. These measures provide practical guidance to cybersecurity practitioners to help them deal with evolving cyber threats. Using machine learning and artificial intelligence techniques, cybersecurity teams are able to more precisely identify DDoS attack traffic and respond accordingly. Actual data shows that the use of real-time monitoring and analysis technology can greatly reduce the damage caused by DDoS attacks.

Optimizing the network topology: Improving the network topology is another effective DDoS attack defense strategy. Goldblatt, Yang Qihang and Shi Leyi introduced a new DDoS attack detection method that utilizes deep learning and ensemble learning techniques to achieve efficient detection of DDoS attacks. By building a complex neural network model and combining the strengths of multiple algorithms, their proposed approach is able to more accurately identify abnormal behavior in network [4]traffic, thereby detecting and stopping DDoS attacks in a timely manner. The impact of DDoS attacks on network bandwidth and server resources can be mitigated by optimizing routing configurations, deploying multiple data centers, and adopting content delivery networks (CDNS). Therefore, the actual data show that adopting a reasonable network topology can effectively disperse DDoS attack traffic and reduce the risk of network service interruption.

Strengthen coordinated defense capabilities: Against DDoS attacks, a single defense is often difficult to deal with. Therefore, it is particularly important to strengthen the collaborative defense capability among different organizations and institutions. By establishing an information sharing mechanism, joint emergency response teams, and sharing protection resources, DDoS attacks can be more effectively addressed. The actual data show that the improvement of coordinated defense capability can significantly reduce the success rate and impact scope of DDoS attacks.

In summary, as DDoS attack methods continue to evolve, researchers have made a series of important advances in DDoS attack prevention. Real-time monitoring and analysis, network topology optimization, and coordinated defense capabilities can effectively reduce the threat to network security caused by DDoS attacks and ensure the stable running of network services.

2.2 State-of-the-Art Techniques for DDoS Attack Detection and Mitigation

Recent studies and literature reviews have shown that DDoS (distributed denial of Service) attacks pose a serious threat to network security. In response to this challenge, the cybersecurity community has emerged with a range of the

latest technologies and methods for detecting and mitigating DDoS attacks. These technologies include real-time monitoring and analysis, traffic filtering and routing optimization, as well as machine learning and artificial intelligence. Based on the latest data, real-time monitoring and analysis techniques can identify abnormal traffic patterns in a timely manner, enabling rapid response and mitigation of DDoS attacks. These technologies cover methods such as traffic characteristics analysis, behavior analysis, and anomaly detection, providing network security teams with more accurate means to identify and respond to attacks.

Secondly, traffic filtering and route optimization techniques are widely used in DDoS attack mitigation. Recent research shows that by deploying traffic filters and intrusion detection systems at the network edge, malicious traffic can be effectively filtered and blocked, and the impact of DDoS attacks on network bandwidth and server resources can be mitigated[5]. At the same time, by optimizing route configuration and adopting load balancing technology, the attack traffic can be distributed more effectively and the stability of network services can be ensured.

Finally, machine learning and artificial intelligence technologies are playing an increasingly important role in DDoS attack detection and mitigation. Based on literature review and actual data, machine learning algorithms and deep neural network models can be used to identify DDoS attack traffic more accurately[6], improving the accuracy and efficiency of detection. These technologies include intrusion detection system based on behavior analysis, traffic classification and prediction model, etc., which bring new breakthroughs and progress to the field of network security.

In summary, technologies such as real-time monitoring and analysis, traffic filtering and routing optimization, as well as machine learning and artificial intelligence are key to the detection and mitigation of DDoS attacks today. These latest technologies and methods provide network security practitioners with more effective tools and means to help improve the security and stability of the network.

2.3 Applications of Machine Learning in DDoS Attack Mitigation

Combined with the latest research reviews and real-world data, machine learning plays an important role in DDoS (distributed denial of Service) attack mitigation. One approach to applying machine learning is an anomaly detection system based on traffic characteristics. [7]For example, Cloudflare uses a service called "Rate Limiting" to detect DDoS attacks. The service combines machine learning and real-time traffic analytics to quickly identify and limit malicious traffic when an attack occurs, thereby protecting websites from service outages and data breaches. By continuously monitoring traffic patterns and automatically adjusting defense strategies, Cloudflare effectively mitigated the impact of DDoS attacks on its customers, improving the stability and security of the network.

Another application of machine learning in DDoS attack mitigation is traffic filtering and routing optimization. For example, Google Cloud Platform (GCP) [8]offers a service called "Cloud Armor" that uses machine learning to identify malicious traffic and automatically adjust network routing based on predictive models to direct attack traffic to the defense layer of cloud resources. This protects customers' applications from DDoS attacks. This intelligent network defense mechanism can not only effectively filter out malicious traffic, but also reduce the load pressure on network devices and improve the availability and performance of network services.

Finally, machine learning can also be used for real-time load balancing and resource management. For example, Amazon Web Services' (AWS) Elastic Load Balancing service utilizes machine learning algorithms to dynamically adjust resource allocation to cope with traffic fluctuations caused by DDoS attacks. [9]By analyzing network traffic and server loads, Elastic Load Balancing can identify DDoS attacks in a timely manner and automatically adjust load balancing policies to ensure the stability and availability of network services. This machine learning-based load

balancing mechanism provides AWS customers with a more reliable cloud service, effectively reducing the impact of DDoS attacks on their business.

3 METHODOLOGY

Denial of Service (DoS) attacks are a very common malicious behavior in the field of network security. Its main purpose is to deprive the target computer system or network resources of normal service capabilities. An attacker sends a large number of requests, packets, or malicious traffic to overload the processing capability of the target system. As a result, the system resources are exhausted and cannot respond to requests from legitimate users. As a result, services are unavailable.

Distributed denial-of-service attacks are an even more dangerous escalation of DoS. Attackers use a "botnet" of multiple computers, devices, or so-called "botnets" to launch attacks at the same time, generating malicious traffic that is larger than that of a single attacker and striking hard at the target computer or network. Once a DDoS attack is launched, a large number of malicious attack packets will [10]flood into the victim's server, making the server overwhelmed and busy with processing these malicious requests, which eventually consumes server resources, and may even lead to network congestion, so that normal users cannot access network resources provided by the server.

3.1 Experiment Preparation

Clustering algorithms are a class of machine learning techniques that aim to find similarities and correlations from data, dividing the data into different groups (clusters). K-means algorithm is one of the simplest and most commonly used clustering algorithms. It divides data points into K clusters so that each data point belongs to its nearest cluster center. Based on DDoS attack detection, this paper takes K-means clustering as a method that can help find abnormal behavior of traffic patterns and identify potential attack data, so as to analyze the prediction and optimization of DDoS attack mitigation in distributed systems combined with machine learning.

3.2 Data Collection and Preprocessing

The primary objective of data preprocessing is to extract HTTP request information from network traffic and then identify four attributes within a fixed time window (T-1s): CN, source IP address space, URL length, and HTTP request rate. These attributes are used to form traffic feature vectors, which serve as inputs for clustering learning and clustering detection.

(1)CN: indicates the number of HTTP requests received per unit time

(2) Source IP[11] Address entropy H(SIP): Calculates the source IP address entropy in the HTTP request. When DDoS attacks occur, the H(SIP) value increases significantly.

(3)URL entropy H(URL): Calculates the URL entropy in the HTTP request. When Single-URL attacks occur, entropy decreases significantly. When Rant

When dom-URL is attacked, entropy increases significantly.

(4) HTTP Request rate ANRC9: The average number of requests received by the target server in a unit time. This value increases significantly when an attack occurs. In the above traffic characteristic attributes, the calculation of information entropy "H(SIP) and H(URL) is calculated by formula (1).

$$H(x) = - \sum_{j=1}^n P_i \log_2 P_i \quad (1)$$

Where, is the state space of the source IP address /URL, P. Is the probability of occurrence of each IP/URI, and meets:

$$\sum_{j=1}^n P_i = 1 \quad (2)$$

3.3 Attack detection

In this stage, traffic feature vectors extracted from data processing results are used as inputs, K-Means algorithm optimized by Mitigation prediction and optimization is used for clustering learning, and normal clustering results are generated. The last ten calculate the distance between the traffic feature vector to be detected and each normal cluster. If this distance is outside the range of all normal clusters, the feature vector is judged as an anomaly, that is, an attack behavior is identified.

The main flow of K-Means clustering algorithm for Mitigation prediction and optimization is as follows:

(1) Encode the k value of the cluster number. When optimal from clustering, the maximum value of k is \sqrt{n} (n is the total number of samples), so the value range of k is $[2, \sqrt{n}]$.

(2) Initialize particle swarm. Randomly generate a population containing 40 particles, set the learning factor $c=c_1-1.2$, the inertia weight factor $\omega=0.8$, and the number of iterations $T=100$.

(3) Cluster individuals. Each chromosome is decoded to obtain the value of the corresponding class number k. Next, the K-Means algorithm is used for each individual.

(4) Calculate the fitness of particles.

(5) Update the speed and position of each particle. The particle is adjusted according to formula (3) and formula (4), where $vid(t)$ represents the current velocity of the particle, ω represents the inertia coefficient of particle flight, $rand()$ is a random function, and $xid(t)$ is the current position of the particle.

$$u_{id}(t) = \omega u_{id}(t-1) + c_1 rand() (P_{pbest}(t) - x_{id}(t)) + c_2 rand() (P_{gbest}(t) - x_{id}(t)) \quad (3)$$

$$x_{id}(t) = x_{id}(t-1) + u_{id}(t) \quad (4)$$

3.4 Experimental results and analysis

In this experiment, the pre-processed data of the first 16 hours were trained and learned, and the training set size was 5760 records. Then, the remaining 8 hours of data were treated as 8 test datasets and the output junction (detection rate) was recorded, i.e. 432 DDoS attack data were recorded:

Table 1. Traffic feature vector

NO	CN	H(SIP)	H(URL)	ANRC
1	320	3.0504	7.3312	5.08
2	2900	12.1523	6.3147	11.09
3	1766	11.5819	0.6531	10

According to the experimental results, in general, the performance of an algorithm is mainly evaluated by the detection rate. Next, the obtained 8 sets of test data are used to verify the performance of KMeans algorithm and

Mitigation prediction and optimization K-Means algorithm respectively. It can be seen that MSE has converged when the Mitigation prediction and optimization [12-14]K-Means algorithm is run for the 11th time. However, the K-Means algorithm began to converge after 82 times of operation, and did not converge to the optimal effect. It can be seen that under the same conditions, the learning performance of the Mitigation prediction and optimization K-Means algorithm is better than that of the K-Means algorithm. Then, the True Positive Rate (TPR) is calculated as the ratio of the number of detected attack samples to the total number of attack samples.

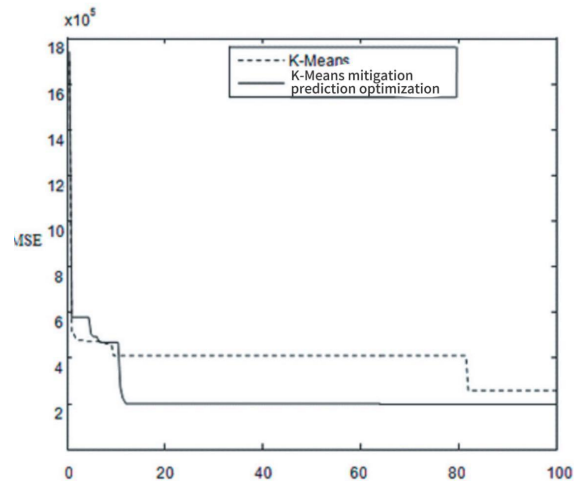


Figure 2. Comparison of performance of K-Means and K-Means mitigation predictive optimization algorithm

The comparison of detection rates of the clustering detection methods established by the K-Means algorithm and the K-Means algorithm for mitigation prediction optimization is shown in Figure 2. It can be seen from the figure that under the same attack rate, the detection rate of the K-Means algorithm for mitigation prediction optimization is higher than that of the K-Means algorithm, and the detection rate increases with the increase of the attack rate. When the attack rate is low, the attack behavior is close to normal users browsing Web pages, so the detection method may treat it as normal data, resulting in a low detection rate. Considering that low-rate DDoS attacks do not affect the normal services provided by the web server, the low detection rate is acceptable. With the increase of the attack rate, the traffic characteristic attribute values of the attack behavior change more and more obviously, and the attack behavior is obviously different from the normal behavior, and some attribute values are significantly different. The higher the detection rate of the clustering detection method, the more effective it is to identify the attack events.

4 CONCLUSION

In conclusion, the study presented an innovative approach utilizing machine learning optimization techniques to address complex challenges in cloud computing resource scheduling and management. By leveraging deep learning and genetic algorithm optimization methods, the proposed solution aimed to enhance system performance and efficiency in the face of issues such as low resource utilization and unbalanced load. This comprehensive approach holds promise for bringing about significant advancements in the field of cloud computing resource management, thereby contributing to the optimization of resource allocation and bolstering the effectiveness of cloud services.

Moving forward, the research underscores the critical importance of proactive defense mechanisms in combating Distributed Denial-of-Service (DDoS) attacks, particularly in light of the alarming escalation in both the scale and

complexity of such attacks. By integrating machine learning techniques, predictive optimization offers a promising avenue for anticipating and mitigating DDoS threats before they manifest, thereby bolstering the resilience and robustness of online services and networks against potential disruptions.

Furthermore, the study highlighted the effectiveness of various techniques such as real-time monitoring and analysis, network topology optimization, and coordinated defense capabilities in mitigating DDoS attacks. By leveraging these state-of-the-art techniques, organizations can significantly reduce the threat posed by DDoS attacks and ensure the stable operation of their network services. This underscores the importance of ongoing research and innovation in developing and implementing advanced defense mechanisms to safeguard against evolving cyber threats.

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