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Securing Cloud Workloads: An In-Depth Study of Cloud Workload Protection Platforms and Their Impact

Prithviraj R[1], R.Saminathan[2], Manishankar R[3]

Abstract

With more and more of the workloads being migrated to the cloud, organizations are in need of stronger security solutions to keep pace with ever changing threats. This study offers an in-depth investigation on the security of workloads of multi-cloud and hybrid environments, while focusing on Cloud Workload Protection Platforms (CWPP) and their effect on securing workloads in multi-cloud and hybrid scenarios. The core CWPP functionalities of vulnerability management, compliance monitoring and runtime protection are thoroughly investigated. This research conducts a detailed comparative evaluation of market leading CWPP providers, highlighting the key differentiating performance, scale, and adaptation of security risks. In pursuit of advancements in the current understanding of CWPPs, the study presents a novel Dynamic Threat Profiling (DTP) methodology with capacity to detect and mitigate Advanced Threats (ATs) dynamically, by dynamically adjusting security policies using real time threat intelligence and workload behavior analytics. In a controlled multi-cloud environment, this method was tested, and has shown great improvement in both detection accuracy and response time compared to traditional static protection models. In addition, the research investigates the integration of CWPPs into DevSecOps pipelines, which demonstrate how continuous security automation incurs benefits for the overall cloud security posture. The research highlights the key importance of CWPPs not just to harden cloud defenses, but also to facilitate more resilient, adaptive and scalable security architectures. The results of this study add to the knowledge base of cloud security by both a comparative analysis and experimental validation of innovative approaches for enhancing the efficacy of CWPPs in dynamic cloud environments.

Keywords: *Dynamic Threat Profiling, Cloud Security, Cloud Workload Protection Platforms, CSPM.*

Introduction

Cloud computing truly demolished the way organizations tackle and deploy their IT infrastructures, delivering greater flexibility, scalability and cost efficiency. But with this transformation comes the need to secure a myriad of security challenges, especially with respect to securing cloud workloads. The primary targets for cyberattacks are increasingly cloud workloads—virtual machines, containers, databases, applications of all kinds, running on cloud infrastructures. Given that these workloads' data is sensitive and critical for business, and are the source of many essential operational needs, security is critical. Conventional security mechanisms simply can no longer manage within the fast changing cloud attacks landscape that require the development of sophisticated dynamic security frameworks which are able to detect, profile and neutralize threats in real time.

Leading this evolution is the advent of Cloud Workload Protection Platforms (CWPPs), a class of security solutions built for cloud native applications, hybrid environments and multi cloud architectures. Although CWPPs offer basic security controls like vulnerability scanning, compliance monitoring and run time protection, the level of sophistication and agility in today's attacks demand more sophisticated and dynamic techniques. One such methodology is Dynamic Threat Profiling (DTP), that brings the power of real time threat intelligence, machine learning based behavioral analytics, and automated security response for protecting cloud workloads. Traditional CWPPs suffer from limited ability to adapt to threats as they evolve, and as such, DTP hopes to overcome these shortcomings by dynamically

[1]Research Scholar, Dept. of Computer Science and Engineering, Annamalai University Annamalainagar – 608002. Email: prithvirajraja4@gmail.com (corresponding author).
[2] Professor, Dept. of Computer Science and Engineering Annamalai University Annamalainagar – 608002. Email: samiaucse@yahoo.com.
[3] Research Scholar Dept. of Computer Science and Engineering Annamalai University Annamalainagar – 608002. Email: manishankar6093@gmail.com

customizing security to handle emerging threats and by catering to the individual behavioral (e.g., the amount of code executed) characteristics of workloads.

Cloud Security Threats Evolution

Over the past decade there have been large changes in the landscape of cloud computing which have seen widespread adoption of cloud native architectures and multi cloud environments. As this shift has brought new complexities to cloud security, case in point, cloud security for workloads that span multiple cloud providers, both public and private and hybrid. The opportunities for customers and vendors are discussed to partner together to achieve cloud security at scale and create true enterprise security capabilities. When cloud was first adopted, during those early stages, the security concerns were around simple infrastructure vulnerabilities like unpatched servers, poor or no access controls, and storing data insecurely. While the issues in question are still present, cloud environments have become far more sophisticated in terms of threats, to the point that traditional security measures can sometimes fail at addressing those dangers [10-11].

As cloud workloads are becoming increasingly dynamic and distributed, one of the key challenges is the increased cost to provision and manage these workloads, which also increases an organization's vulnerability to outages. Cloud workloads tend to be much more dynamic versus traditional on premise based environments where IT assets tend to be much more static and predictable. Cloud workloads will tend to spin up and spin down due to demand. Applying traditional security controls intended for static infrastructure to the ephemeral nature of resources within a cloud environment that has containers and serverless functions complicates the process. As a result, cloud native applications are microservices that are containerized and deployed across multiple regions, each microservice using APIs to communicate. In this way, these services are highly interconnected, giving attackers numerous avenues by which to attack, greatly expanding their surface area for possible breach [13][15].

At the same time, advanced persistent threats (APTs) [17] are becoming increasingly transparent and increasingly hard to detect while targeting cloud workloads. Today's attackers are using automation, AI, and machine learning to exploit those vulnerabilities more efficiently in these cloud infrastructures. While APTs are no longer limited to leveraging one attack vector (such as brute forcing a password on a misconfigured server), they frequently involve multi stage attacks against traditional defenses that leverage weaknesses in cloud orchestration [19], identity management and configuration. An attacker may start with an innocuous cloud service misconfiguration, escalating privilege and then moving laterally in the cloud environment, culminating with the exfiltration of sensitive data or surplus with backdoors for future exploitation [28].

In addition, since the prevalence of insider threats has been growing with the adoption of the cloud environment, especially in multi-tenant architecture where a number of organizations use the same physical cloud infrastructure simultaneously. Validly accessing cloud workloads either through compromised credentials or with mal-intent are insiders to be considered with risk. It's difficult for traditional security mechanisms to detect anomalous behavior, since these attackers are already in control of an organization's cloud resources and already have authorized access. The concern continues to grow of these attackers evading detection as they blend in with normal traffic and operations [30-31].

The second major problem is that traditional security approaches don't work easily with cloud native environments. The security solutions that have been developed for on premise infrastructures, including firewalls, Intrusion Detection Systems (IDS), and antivirus software, have been retrofitted for the cloud [26]. And yet many then don't provide the required agility and scalability to protect against cloud threats today. Take for example traditional firewalls and network perimeter defenses, these are ill suited for securing workloads in cloud environments where perimeter itself is fuzzy. With cloud native applications being highly distributed and the broader use of DevOps and DevSecOps [20] pipelines to develop and deliver applications faster, security must be incorporated continuously and with dynamism across the entire cloud stack [27].

Cloud Workload Protection Solutions

In the early days of cloud security solutions, the mentality was about perimeter based defenses, things like cloud access security brokers, anomaly detection [3] and basic identity and access management controls [20]. Cloud Access Security Brokers (CASB) work as intermediaries between cloud service providers and cloud service consumers to enforce security policies on access to data, data encryption and compliance. CASBs are useful for helping you monitor user access to cloud

services, but being data layer tools, they are inherently limited in their ability to secure workloads themselves, since CASBs have limited knowledge and visibility in the behavior of cloud native applications [21].

CSPM solutions came into prominence in subsequent advancements in cloud security. CSPMs become a tool to automatically detect misconfigurations in cloud environment like an open storage bucket, insecure identity policies, not patched vulnerability and so on. These are useful security tools that scan for known issues and force proper security hygiene with both known and unknown issues in the cloud. But CSPMs are not sufficient to deal with more advanced threats, such as those that exploit runtime vulnerabilities or attack advanced, cloud architectures [22-24].

These CWPPs were developed in response to those limitations and in an effort to present a more holistic view to cloud security. CWPPs provide a multitude of capabilities that includes vulnerability management, runtime protection and compliance monitoring tailored for cloud native applications. Security in CWPPs is extended beyond the perimeter, and covers the workloads themselves irrespective of where they would be run—on premise, in public Clouds, or hybrid Clouds [25]. To overcome these limitations, this paper introduces the inclusion of Dynamic Threat Profiling (DTP) into cloud security architectures as an additional layer of protection for cloud workloads. With DTP departing from static detection model to a more dynamic, adaptive approach, it's a big evolution from the security standpoint.

Dynamic Threat Profiling is a comprehensive security framework built on top of a real time threat intelligence, machine learning based behavior analytics and automated security response. Unlike traditional CWPPs these rely on statically defined security policies and signatures DTP continuously updates its threat profile using the latest available intelligence both from within and from external sources. DTP can detect anomalies, even if they don't match any known signatures, by correlating threat intelligence in real time with workload behavior analytics. Another advantage of DTP is its capability to flex with the behavior of cloud workloads. A different usage pattern exists depending on the type of cloud workload whether in a containerized or serverless: cloud workloads may have different functions or resource demands. For example, an application of machine learning may have high CPU usage during training but low CPU usage during inference and may run on a server side that sits in the cloud. Whereas DTP, using machine learning, can determine what's normal workload behavior vs what is abnormal activity, and so can flag for investigation. Another important feature of DTP is its ability to be directly integrated with real time threat intelligence. Traditionally, CWPPs run in silos, using their own proprietary means to discover threats. Contrarily, DTP is continuously feeding on external threat intelligence from a variety of sources: threat intelligence platforms (TIPs), security information and event management (SIEM) systems, and feeds from other third party security organizations. By this integration, DTP will be able to maintain the latest intelligence on attack vectors, malware trends and threat actors, and applying that intelligence, DTP will be able to proactively defend cloud workloads before they are impacted.

Problem Statement & Motivation

Traditionally, CWPPs, CSPMs, and CASBs all fell into one category of generation of cloud security solutions. These all had many of the previously mentioned challenges, and so would struggle to provide true end-to-end protection in the modern cloud. One of the main limitations was the presence of signature based detection methods, which are always inherently reactive. However, signature based systems can only detect known threats for which specific signature exists. Because they aren't effective against zero day vulnerabilities including advanced malware that can pinpoint through signature based detection by methods like polymorphism, or obfuscation [29].

Also, traditional cloud security solutions can't scale efficiently in dynamic, multi-cloud environments [26-27][29]. With more and more organizations operating in a multi-cloud world, the security tools are need to employed to provide homogeneous security across a myriad of cloud platforms, each with their own specialized set of configuration and security policies. As CWPPs, they can provide a native, individual workload focused security, however due to their individuality, they struggle to provide a unified protection path along an endless variety of cloud service combinations without significant complexity and management headache.

And, the challenge of previous generation solutions failed because there was no automation and no real time response. In most cases, security incidents would demand human intervention, resulting in delay in threat mitigation and leaving workloads open to attack. For instance, in the case of a vulnerability identified in the cloud workload, traditional security tools will raise an alert but no capability

to automatically apply a patch or isolate the workload is available to do so. The problem with this delay in response can be catastrophic, especially for fast moving threats like ransomware or DDoS attacks.

Finally, traditional security tools were siloed limiting their effectiveness when using cloud solutions. But often the tools operate independently from each other, forcing a security practitioner to correlate information across various layers of the cloud stack. For example, a CSPM may detect a misconfiguration on a cloud storage bucket but, without integration with a CWPP, may not be able to identify that configuration has been exploited to compromise a workload. For example, an unauthorized access to a cloud service may be discovered by a CASB but not the behaviour of workloads underneath by which the access was granted and in this way determine if a security breach occurred.

Contributions in this paper

- A novel approach to real-time cloud workload protection by leveraging advanced machine learning and behavioral analytics.
- The integration of real-time threat intelligence with DTP, enhancing the detection and mitigation of emerging threats within cloud environments.
- A comprehensive evaluation of DTP's impact through real-world experimentation on Amazon Web Services (AWS), illustrating its effectiveness in improving cloud security.
- This paper highlights the automation of security responses, reducing manual intervention and enhancing operational efficiency.
- This research underscores the importance of seamless integration between workload behavior analytics and existing cloud security mechanisms, displaying how these technologies can work in tandem to provide a robust defense against sophisticated cloud-based attacks.

Literature Survey

Due to the dynamic nature of cloud application workloads, workload prediction, which has been recognized as an essential element within PSoM frameworks, brings in serious challenges. Traditional techniques decompose workloads into trend, seasonal, and random parts, and model each of these components separately, but the random component tends to introduce substantial noise and heteroscedasticity, detrimental to model accuracy. A new ensemble model, FAST, combining trend and seasonal components as macro changes and employing an adaptive sliding window algorithm for micro workload changes, are proposed. It contains an adaptive sliding window algorithm that both accounts for trends and time correlations and random fluctuations to achieve online regression with high accuracy and reduced overhead. An error based integration strategy is proposed, utilizing time locality, which enables local predictor behaviors by means of a multi class regressor. Experiments against Google cluster trace datasets is conducted and show that FAST achieves better accuracy than other state of the art models for dynamic workloads [1]. To explore the edge computing realm, cooperative edge-cloud computing paradigms are established in the population of geographically distributed edge datacenters that optimize service latency among edge users. Virtual machine placement and workload assignment are explored as a problem of minimizing IT infrastructure consumption under various applications' latency requirements, and a mixed integer linear programming model is proposed for this purpose. [2] Effective cross site VM placement and workload redirection can also enhance resource efficiency per preliminary results.

To deal with complexities of workload forecasting in heterogeneous and dynamic cloud environments, An E-LCWF framework is introduced. In this direction, this framework models individual resource workloads as multivariate time series, and uses anomaly detection and an error based ensemble approach coupling the machine learning based transformer and Long Term Time Series Forecasting (LTSF) based linear models to improve forecasting performance. The ELCWF framework leads to significant improvement over existing models in forecasting accuracy. An adaptive future workloads prediction model, called a Super Markov Prediction Model (SMPM), based on adopted workload patterns, has been developed. The model performances were evaluated against various datasets, such as Alibaba trace and Google Cluster Trace, and shows better accuracy than available prediction models in terms of Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) [4].

Another highlight is the importance of real time workload prediction in cloud computing and point out the challenges in predicting heterogeneous and unpredictable workloads. While these algorithms are becoming popular in workload prediction, they are known to be vulnerable to adversarial attacks.

The vulnerability of these advanced deep learning models are explored, RNN, LSTM, GRU and 1D-CNN, to adversarial examples obtained from modern computer vision methods. From cloud benchmark datasets, The deep learning based forecasting models are especially vulnerable to adversaries, requiring the development of robust defenses for cloud workload forecasting [5]. Another work by [6] discusses about the workload characterization and prediction for maintaining resource elasticity and scalability in cloud data center. This paper provides a detailed literature review on the existing workload prediction solutions in terms of application oriented clustering and challenges posed by workload variability and heterogeneity. Additionally, the study finds open research opportunities to improve the workload prediction methodologies [6]. A novel approach to predict turning points in cloud workloads, i.e., points in time when the workload changes direction and fluctuates critically is proposed by Ruan et. al. [7]. In this work, upon traditional prediction methods using the unique features of cloud computing are improved within a deep learning framework. This method is then shown to be effective as compared to contemporary trends, validating it via experimental validations on the Google cluster dataset [7], which is the first systematic investigation into the problem of use of turning point based trends for cloud workload prediction [7]. As network security developments evolve from traditional security measures, to adapting to the mobile networks, cloud computing and Internet of Things (IoT) technology breakthrough, it becomes necessary. Network security, as highlighted in a recent study shows that the network security core objective has transitioned not only to ensure data transmission is safe, but also to assist in cloud based information services. A cloud–network–end collaborative security architecture was proposed against these changes. This architecture addresses three critical areas: The three security elements comprise of end system security, network connection security, and cloud services security. The authors illustrate this framework through a number of applications including an Unmanned System Collaborative Operations Security framework and a heterogeneous network secure convergence framework. They also survey related research about security mechanisms in these domains, highlighting the need for approaches to evolve to achieve strong security in the modern network environments[8].

Privacy in the context of Mobile Cloud Computing (MCC) has become a even more fundamental security issue than before because of the risk of malicious or colluded cloud servers exfiltrating sensitive data from computation parties. To deal with these challenges, a privacy preserving cloud assisted two party computation scheme is introduced based on an optimized half gate method. Notably, this work is the first to resist all collusion attacks in a malicious model, which improves data exchange's security. Our security analysis proves the scheme to be correct and fair, and performance comparisons show that it significantly reduces the communication costs of such schemes, taking up to 96.8% less communication cost than currently known solutions [9]. Also, due to the wide spread of cloud computing now, there are serious issues on data security and user authentication. In this paper, a dual approach is proposed combining a fragment technique with a NoSQL database to prevent unauthorized access to data stored in public clouds. The authors also propose a multimodal biometric authentication system that allows the management and authentication of users, whose biometric features are protected. While the devised fragmentation method shows favorable latency performance than that of usual encryption methods, it is relatively favorable for latency sensitive environments such as healthcare IT infrastructure [12].

Another paper [14] demonstrates a multi-qubit Quantum Key Distribution (QKD) model that is integrated with Ciphertext-Policy Attribute-Based Encryption (CP-ABE) in order to improve security in cloud environments. This model takes advantage of quantum cryptography principles to produce secure keys to encrypt and decrypt data keys based on user attributes. Simulation model results show that quantum cryptography has promising potential in securing cloud data against unauthorized access [14]. Also, there has been a large growth in market penetration of Infrastructure-as-a-Service (IaaS) and the importance of controlling cost, as well as ensuring good security and user experience, is becoming critical for cloud service providers. In this research, a two stage algorithm which comprised a security service selection scheme and an improved firefly algorithm is proposed for workflow scheduling. Extensive simulations show that the approach proposed in this paper can achieve up to 57.6% cloud service cost savings without sacrificing security or efficiency, resulting in a more satisfactory user experience [16]. Another work to integrate IoT with cloud computing is proposed [18] to revolutionize different applications by facilitating functionality and information access exists. While rapid cloud migration has brought about many new security challenges. In this research, it will investigate how by incorporating the IoT initiatives in conjunction with cloud technologies some of these barriers will be availed, especially when using blockchain technology to enhance data integrity, privacy and secure transactions on a highly distributed shared platform [18].

Given these challenges, there is a clear need for a more integrated and adaptive approach to cloud workload protection. Dynamic Threat Profiling, as proposed in this paper, addresses the shortcomings of previous-generation solutions by providing real-time, behavior-based threat detection, automated response capabilities, and integration with external threat intelligence. This approach ensures that cloud workloads are continuously protected, even as the threat landscape evolves and new vulnerabilities emerge. In addition to enhancing security, DTP offers several operational benefits for organizations. By automating security responses, DTP reduces the need for manual intervention, allowing security teams to focus on more strategic initiatives rather than reacting to individual incidents. Furthermore, DTP's machine learning-based analytics can help organizations optimize their security posture by identifying inefficiencies in their cloud environments, such as over-provisioned resources or misconfigured access controls.

In conclusion, the rapid evolution of cloud computing demands a corresponding evolution in cloud security. Dynamic Threat Profiling represents a significant advancement in this regard, offering a proactive, adaptive approach to protecting cloud workloads from modern threats. This paper explores the implementation of DTP within cloud environments, leveraging real-time experimentation on Amazon Web Services (AWS) to demonstrate its efficacy in securing dynamic, multi-cloud architectures. Through the integration of machine learning, real-time threat intelligence, and automated security responses, DTP provides a comprehensive solution for addressing the security challenges posed by modern cloud workloads.

Proposed Methodology: Dynamic Threat Profiling (DTP) and Real-time Threat Intelligence with Workload Behavior Analytics

In the fast-paced world of cloud computing, security is not something that gets taken care of after the fact, but it needs to become a fundamental pillar of the cloud architecture. Complex security challenges have been introduced by the dynamic nature of cloud environments and especially when combined across hybrid and multi-cloud architectures. More and more, cyber attackers focus on cloud workloads, defined as applications, services, and data running in the cloud, by attacking vulnerabilities in real time when discovered. This is a new type of attack and traditional static security controls are not sufficient to assist; however, Cloud Workload Protection Platforms (CWPP) are becoming an essential part of a cloud security strategy since they can effectively assist to detect these emerging threats. Vulnerability management, runtime protection, and many more features are available on these platforms; the attacks have become too sophisticated to be defeated with the approach they offer.

The Dynamic Threat Profiling (DTP) methodology is where this comes into its own. Traditional CWPP can be enhanced with DTP; integrating real time threat intelligence and leveraging workload behavior analytics to deliver an active, adaptive, and responsive security posture for cloud environments. In this discussion, a key principles of DTP that interplay in a real time threat intelligence enabled environment utilizing workload behavior analytics are discussed. Together, these elements provide a powerful defense mechanism that not only monitors, but also defends cloud workloads proactively from rising threats.

Dynamic Threat Profiling (DTP) Methodology: An Overview

Dynamic Threat Profiling (DTP), a security methodology designed for deploying effective real time protection and adaptation in cloud environments, is the focus of our solution. Unlike any traditional security mechanism that relies on predefined rules and static policies, DTP changes as it continuously monitors cloud workloads, analyzes the threat vectors, and dynamically changes its security response. Its value comes from being especially suitable to cloud environments because they are by their nature dynamic, where workloads and data flows flow in and out of multiple cloud platforms and geographies. Adaptive threat profiling represents the foundation of DTP. In this system threat profiles are generated and updated in real time on continuous monitoring of workload behaviour, known threat patterns and real time threat intelligence shared from other external sources. DTP is based on the principle that security is an ongoing process; profiles are not fixed, but change in response to new threats or over time as the nature of the workload changes. This evolution is driven by considering the interaction between the workload and the rest of the cloud infrastructure, with the aim of detecting anomalies indicative of pending threats. Figure 1 shows the architecture of the Dynamic Threat Profiling. DTP operates in three key stages namely.

Threat Detection and Profiling

The first thing in this stage is real time workload monitoring to detect any abnormal behavior or activity. Machine learning algorithms and behavioral analysis is the basis of the system, which can detect deviations from normal workload behavior, such as that of potential threats. These anomalies are profiled further, developing a dynamic threat profile which updates with additional data.

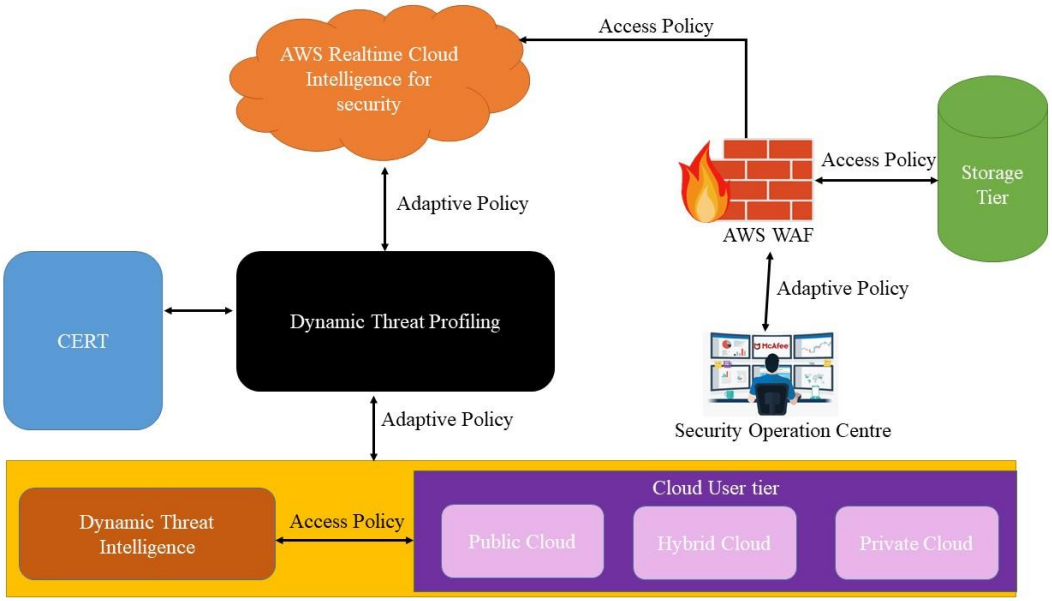

Figure 1. Architecture of Dynamic Threat Profiling

Threat Intelligence Integration

Once there is a threat profile, the system uses real time threat intelligence feeds. Open source threat dataset, feeds are taken from open source threat databases, Cloud security providers, and proprietary intelligence platforms. Once integrated, this intelligence can be used to turn a DTP system into a force multiplier by putting the threat into context of a broader canvas of known cyber attacks, to help determine whether it is indeed part of a larger attack campaign, or a fend new threat.

Automated Response and Policy Adjustment

DTP dynamically changes security policies across through the cloud environment based on profiling and contextualization of the threat. Some of this can be as simple as automatically adjusting firewall settings, isolating affected workloads or updating security rules for incoming workloads. The dynamic adjustment guarantees that the response to the security problem is not only timely but also adapted to the specific properties of this threat. DTP is an adaptive solution, which also means that it is learning from new threats and refining its threat profiles consistently. It drastically boosts the security posture of cloud environments by providing an adaptive and evolutionary layer of protection that can scale across multi cloud and hybrid infrastructures.

Real-time Threat Intelligence

It is a critical component — the use of real time threat intelligence with the Dynamic Threat Profiling methodology — that helps DTP prevention of sophisticated modern cyberattacks. Threat intelligence in real time is the ongoing feed of information about known cyber threats, attack vectors, vulnerabilities, and malicious actors. It collects intelligence from many sources, such as cloud service providers, security organizations, open source platforms, proprietary databases maintained by cybersecurity vendors. Identify emerging threats: Because DTP receives real time updates with information regarding such new vulnerabilities or attack patterns, detection of threats that haven't already compromised the workload but could threaten in the future, is possible. For example, if one cloud service provider is being the target of a Distributed Denial of Service (DDoS) attack, the DTP system can automatically roll out additional security measures, even if the particular workload is not affected.

Correlate threat activity

DTP can consume real time intelligence to correlate threat activities specific to a region, workload or cloud environment. In Multi-Cloud architectures where workloads are spread across multiple Service Providers, this correlation is very much useful. One region acting as a threat can mean that security measures are undertaken in another, meaning that potential cascades of attacks across the infrastructure may never even get checked.

Enhance threat response

The intelligence gathered allows the DTP system to select the most effective countermesures to the threat that has been targeted. For instance, if an identified ransomware campaign requires real time intelligence then it could mean that stronger encryption policies must be implemented or workloads isolated until the threat can be addressed. To be effective, DTP applies a real time threat intelligence pipeline that regularly ingests and analyzes threat data from many sources. The data analytics and machine learning algorithms fuel this pipeline, which quickly siphons through huge amounts of threat data and delivers actionable insights for the end user. They also help activate the automated response mechanisms in DTP to make these security adjustments as close to event time as possible. In addition, predictive threat analytics are used in the system, analyzing trends in real–time data to predict future threats. By looking at patterns of attack behavior across multiple sources, the system can pick up weak signals of an impending attack in the making. This is also useful in large cloud infrastructures where time provides the margin in stopping an attack from spreading virally and the tools for reacting effectively after widespread damage has already occurred.

Workload Behavior Analytics: Adaptive Security Model

An important part of the Dynamic Threat Profiling methodology is utilizing workload behavior based analytics to detect and mitigate threats in real time. Cloud workloads behavior analytics means the ongoing analysis of their behavior looking for deviations from certain patterns that could infer a security threat. To achieve this, advanced machine learning algorithms, heuristic analysis and baseline behavioral models are combined. Behavioral patterns of cloud workloads vary with the nature of the application, the data being processed in the workload and the environment where the workload works. For example, a typical pattern of data requests, processing, and response requests, seen in a web application workload, is essentially a behavioral baseline from which a workload model may be built. Any deviations from this base, say a higher than normal volume of data requests or an odd reduction in processing speed, might result from a potential security threat, like a DDoS attack or an inside threat that is exfiltrating data. Workload behavior analytics is based on the idea that every workload has a distinct "behavioral fingerprint" that can be constantly watched for signs of anomalous behavior. The following steps outline the process:

Behavioral Baseline Creation

The first step in doing this is to build a baseline of what normal workload behavior looks like by observing activity over a given span. That we gather measurements for (CPU usages, memory consumption, network traffic patterns, user access patterns, etc.) and data flows. These metrics are analyzed by machine learning algorithms to generate a model that represents normal operational behavior for the workload.

Anomaly Detection

After baseline is established, the system is constantly watching workload to detect any deviations from this baseline. A potential anomaly is flagged in any instance in which the activity deviates significantly from the expected behaviour. Advanced algorithms are used by the system to eliminate false positives, so genuine security threats are alerted to for further analysis.

Contextual Threat Analysis

The system performs a contextual analysis of the workload and its environment after detecting an anomaly to decide if the anomaly is indeed a genuine security threat. For example, it may possibly be network traffic spike due to a DDoS attack or may possibly be due to a legitimate business activity. The nature of the threat can be determined by examining the context: does the spike fall in normal business hours or in correlation with normal user activity.

Dynamic Profiling and Response

After behavior analytics identify a potential threat, the DTP system then updates that workload's threat profile in real time. In the case when security threat is detected, it can dynamically update security policies, for example, limiting access, isolating the workload and applying additional encryption as a response. The adjustments to these security measures are made automatically, so that they are appropriately responsive to the characteristics of the threat in question. Workload behavior analytics is a very powerful tool to detect even the sophisticated threats which may slip past traditional signature based security mechanisms. For instance, an Advanced Persistent Threat (APT) is an attack designed to evade detection for many days, which could display slight behavioral changes in the workload that analytics might generate some primitives to detect. Similarly, the insider threats – malicious actors with legitimate access to system – can also modify workloads in ways that depart from the natural behaviors. DTP is able to defend against these threats with adequate response by continuously monitoring workload behavior.

Real time Experimentation & Validation

As cloud adoption grows, the modern cybersecurity landscape is seeing an unwavering increase in the complexity of cyber threats. As organizations continue to move to cloud infrastructure, there is an increasing trend to intelligent security frameworks that can dynamically adapt to changing threats in real time to create a resilient and secure cloud platform. An advanced methodology such as Dynamic Threat Profiling (DTP) promises to use real time threat intelligence and workload behavior analytics to detect, mitigate, and neutralize threats in a cloud environment. An ideal environment to perform real time experimentation based on the DTP with AWS cloud platform would be to monitor, profile and secure the cloud workloads dynamically across multiple use case scenarios. In this experimental setup, cloud services, automated security response and workload protection in the real time are aim to include, and utilize DTP in a real cloud environment to gain some practical insights about the DTP's performance and efficiency.

The real time experimental setup highlights two distinct real-time scenarios using AWS: The first was focused on integration of real time threat intelligence, while the second focused on workload behavior analytics. The two experiments demonstrate how DTP can respond to different kinds of threats while optimizing the cloud workload security posture in a production setting.

Experimental Setup

Real-time experimental setup for the Dynamic Threat Profiling methodology are based on the use of AWS cloud services for monitoring, profiling and securing workloads on the fly. Given that threat detection, analysis, and mitigation is dynamic, the setup includes several AWS services – Amazon EC2 (Elastic Compute Cloud), AWS Lambda, Amazon CloudWatch and AWS Security Hub – integrated to develop an environment which enables detection, analysis, and mitigation of threats. In addition, this experimentation utilizes AWS Machine Learning capability to ascertain workload behavior and real time threat intelligence feeds to improve the efficacy of DTP system. Figure 2 shows the real time experimental setup to dynamically profile workloads in the AWS cloud using the Dynamic Threat Profiling (DTP) methodology.

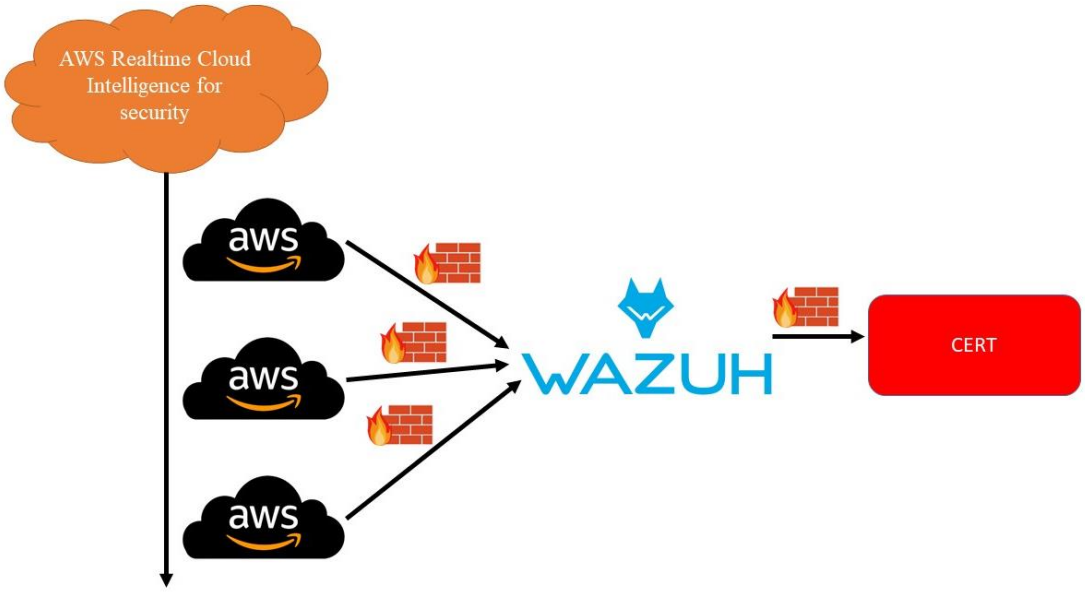

Figure 2. Experimental setup of Dynamic Profile workloads in AWS Cloud using DTP

Since AWS provides elasticity, scalability along with wide array of built in security services which can be integrated with custom security methodologies such as DTP the best place to perform this experiment is with AWS. To assess the operation of DTP in protecting cloud workloads against dynamic threats, two separate scenarios are implemented for this real-time experimental setup.

Scenario 1: Integration of real time threat intelligence

The first case concerns integrating real time Threat Intelligence to identify and react to emerging threats. The goal is to replace a static system currently in use for profiling cloud workloads and responding to known and unknown threats in a real world environment. The experiment starts by provisioning multiple Amazon EC2 instances over diverse regions of AWS. Each of these instances is monitoring in real time with Amazon CloudWatch and AWS Security Hub for critical workloads running business applications. Multiple EC2 instances are used for the experiment, so that the experiment closely mirrors a real world hybrid cloud scenario with workloads distributed across geographies with varying threat profiles across regions. Through the Amazon CloudWatch, the DTP system continuously collects performance metrics, network traffic logs, user activity logs from EC2 instances. The DTP's threat profiling engine is triggered by sending this real time data to AWS Lambda. Finally, the Lambda Function, is a serverless orchestration Engine that aggregates logs and correlates them with external threat intelligence feeds. AWS Security Hub backs up the threat intelligence pipeline, integrating third party feeds such as CrowdStrike, McAfee, and Amazon GuardDuty, among others. The information about emerging threats, known vulnerabilities and attack campaigns that come through these feeds is a continuous stream. If AWS Lambda finds EC2 instances behaving abnormally or under suspicious behavior, the DTP engine correlates it with Security Hub intelligence to ascertain attack likelihood. In this experiment, two types of cyber threats are simulated:

The malware infection which tries to exploit vulnerability in one of the EC2 instance.

- A malware infection that attempts to exploit vulnerabilities in one of the EC2 instances.
- A DDoS attack [launched using a botnet] increasing the network bandwidth of another EC2 instance located in another region.

First a malicious script to one of the EC2 instances is uploaded, which was trying to execute and exploit a known vulnerability in the Operating system and then the malware infection simulation is started. Unusual activity, like unauthorized file access and unexpected CPU spikes, show up immediately on our AWS CloudWatch. These alerts are forwarded by AWS Lambda to the DTP system, and the DTP system correlates the alerts with threat intelligence from Security Hub. It identifies the threat as being part of a persistent malware campaign hitting cloud environments. Then DTP system

dynamically modifies security policies in real time once the malware is identified. The DTP system automates a patch management process with AWS Systems Manager, pushing the latest security patches to close the vulnerability used by the malware. Meanwhile, AWS Shield Advanced is armed to protect the EC2 instance from additional attacks as a means to block any future attempts to exploit the vulnerability.

For the simulated DDoS attack case, the DTP system observes a sudden spike in the incoming traffic toward an EC2 instance in another region. With Amazon CloudFront, the AWS WAF (Web Application Firewall) is enabled to mitigate the DDoS threat by the implementation of rate limiting rules. In addition, traffic is redirected to alternative resources lowering load on the targeted instance and avoiding a downtime. The DTP system revises its threat profile continuously, based on this changing situation of an ongoing attack. For instance, this information is added to the malware threat profile about the specific vulnerability exploited, the IP address of the attacker and the techniques. With this, the system can then proactively defend other workloads against similar threats in the future.

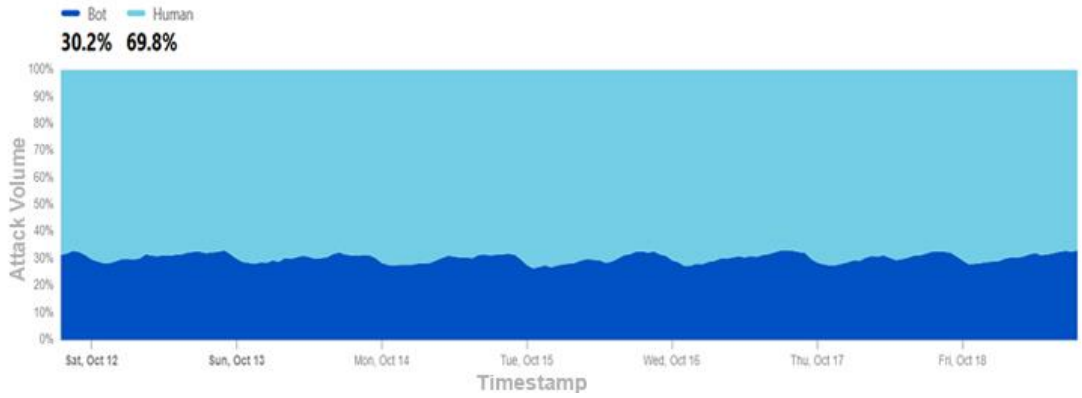

Figure 3. Bot (automated) vs. human HTTP requests distribution

A visualization of HTTP requests distribution generated by automated bots and human users in Figure 3 is provided. In regard to analysis of web traffic patterns as well as detection of possible threats, such as when under a DDoS attack (Distributed Denial of Service), this comparison is vitally important. Finally, as shown in the figure 3 the x-axis is number of time intervals (or requested to special counts) and the y-axis is total number of requests. It is clear that there is a distinction between automated bot requests and human requests and the distribution patterns for each are distinctly different. Often, automated bots that are programmed to perform specific tasks without human intervention, fire off a huge quantity of requests in a blistering amount of time.

A spike in the number of automated requests leads to a hypothesis of possible DDoS attack, i.e. that a botnet — a network of compromised machines — is sending a flood of requests to the target server. Such attacks simply exceed the resources on the server so that the server is unable to process legitimate user requests – disrupting the service. However, human generated HTTP requests are more sporadic and more gradual in their pattern. They exhibit this same property, which is consistent with natural pauses found in human browsing behavior as a result of human cognitive response and decision making. Analysis of these patterns helps cybersecurity professionals build baselines of good legitimate user activity, which gives them a better sense of what anomalous traffic looks like.

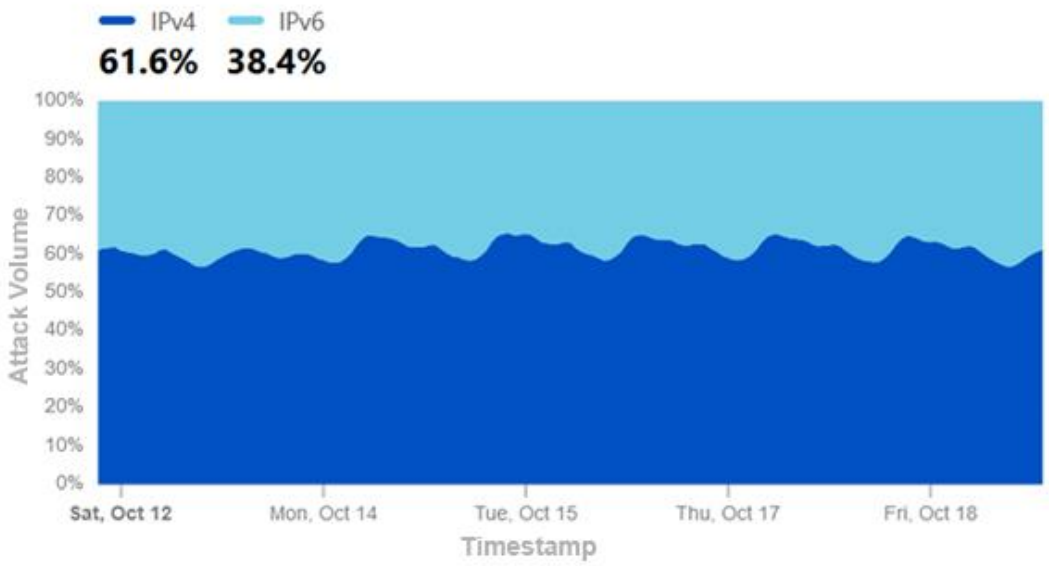

Figure 4. Distribution of HTTP requests by IP version

The distribution of HTTP request traffic by Internet Protocol (IP) version, IPv4 vs. IPv6, is shown in Figure 4. Due to exhaustion of IPv4 addresses, this analysis is especially timely in the context of emerging network standards, and continuing migration to IPv6. In the figure, the x axis classifies the requests by their IP version, and the y axis shows a count of the number of requests received, thus giving a good picture of how these IP protocols are employed in web traffic. IPv4 has historically been the party in charge of internet traffic, and the number is probably a significant number of HTTP requests coming from IPv4 addresses. To understand this prevalence, it is important to note the extent to which the IPv4 infrastructure is subjected to, as not just have a world of devices and users, but a world that keeps relying on IPv4 infrastructure to serve. However, it makes IPv4 networks dependent to several vulnerabilities, as the attackers usually attack systems using protocol weaknesses. Because IPv4 addresses are the higher volume you might say it points to a larger attack surface whereby your attackers might be targeting devices that have not yet moved to IPv6, have not been provisioned to IPv6, or perhaps haven't moved their security with them. Whereas the representation of IPv6 requests in the figure may be very low comparatively, it shows a growing pattern of adoption. With the continuing migration of organizations and internet service providers to IPv6, it becomes more important to observe where requests are coming from. In order to understand more about these two IP versions and how requests are being distributed across them not only helps in identifying potential attack vectors but also helps the cybersecurity professional realise the landscape of web traffic is evolving. Analysis shown in Figure 4 reveals the importance of understanding how HTTP requests received by IP version. HTTP requests by IP version are very important for organizations to understand who is making valid HTTP requests from their corporate network if your mitigations affect them.

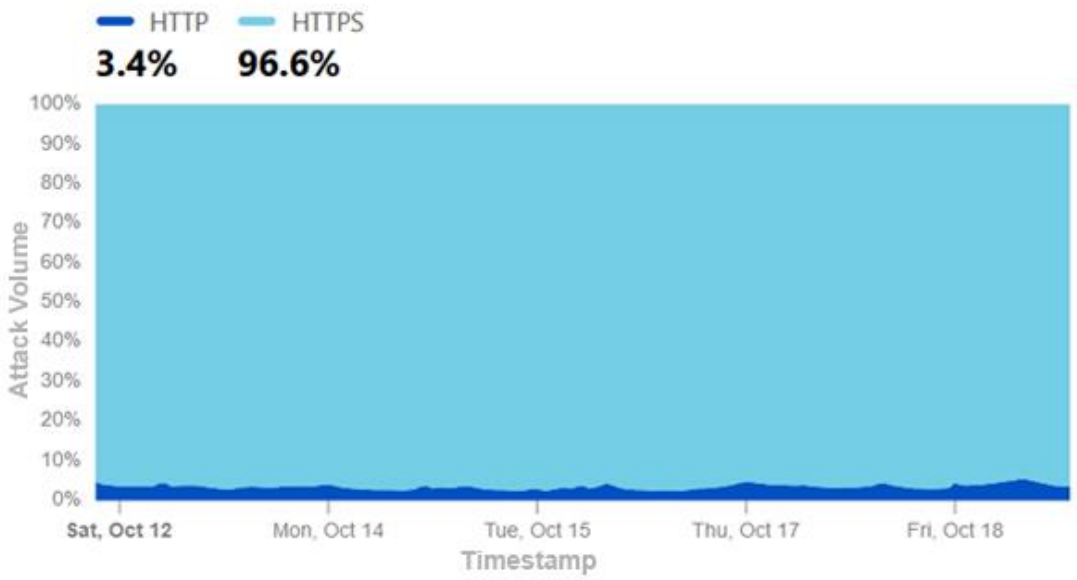

Figure 5. Distribution of HTTP vs. HTTPS requests

Figure 5 compares the distribution of HTTP and HTTPS requests and is critical to understanding the distribution of web traffic particularly related to DDoS experimentation. On this figure, the x-axis relays the breakdown of requests into HTTP and HTTPS, and the y-axis reports the total number of requests the server processes. This is an important distinction in understanding both how secure communications are currently implemented and the effect on the privacy of the user and overall security of the web. Given that HTTP requests are unencrypted, they are vulnerable to kinds of cyber attacks, such as eavesdropping and data manipulation. This figure probably shows a considerable amount of HTTP requests, which means that a lot of systems and websites still use this old protocol. Such relying on the fact exposes users to risk, becoming easily accessible via the Data Center Network (DCN) as malicious actors can intercept and manipulate the DCN, causing severe results, particularly during the DDoS attacks. Attackers can leverage weaknesses in HTTP communications to magnify the affects of their assaults on servers they wish to attack. On the contrary, HTTPS requests, which make use of the encryption to secure exchanges of data between users and server, are becoming more and more the norm for web traffic. It may be that the figure shows HTTPS request growing trend, implying ever increasing adoption of HTTPS by organizations and users which ultimately results in awareness about the need of secure communications. It's a positive development in the use of HTTPS, because that enhances user privacy, and protects against many cyber threats. It is a collective call to secure web applications and services so that the risk of data breaches can be diminished and the confidentiality of user's interaction with web sites can be maintained. The distributions of HTTP and HTTPS request for DDoS mitigation strategies and cybersecurity are closely compared. Since service provider and user security practices improve when more HTTPS traffic is present, it implies a strong security posture that can provide protection against a number of different attack profiles. However, organizations that are seeing a large volume of HTTP requests may want to look at moving over to HTTPS across various platforms their data passes through, to help protect user data and increase their defenses to potential attacks.

Scenario 2: Threat detection through Workload Behavior Analytics

In the second scenario, our experiment involves workload behaviour analytics to observe and react to insider threats or anomalous activities that are not within normal patterns. This is an environment with many workloads all with different user activity, data processing and network traffic. The aim is real time analysis of these patterns to detect anomalies, which could represent a case of insider threat or unauthorized access. The experiment is started by provisioning a set of EC2 instances to setup a web application, a database service, and a machine learning application. Amazon CloudWatch monitors each workload, for CPU usage, memory consumption, disk I/O, network traffic, and API logs. In these metrics, a clear view of how each workload behaves normally so the DTP system can build a behavioral baseline. To analyze workload behavior, the DTP system builds models in Amazon SageMaker, AWS's machine learning service, to predict accurate models of normal behaviour for each workload. For instance, web application workload characteristically sees high traffic during peak hours, while the traffic

is low during off peak hours. SageMaker trains a machine learning model, which becomes the baseline, by finding these patterns. In this experiment, two types of anomalies are simulated.

- A malicious insider threat, where the malicious user has a perfectly valid set of credentials, but still tries to exfiltrate sensitive data from the database workload.
- Attack scenario when an external attacker takes control of the account with access to the machine learning workload and tries to change the training dataset.

The insider threat is simulated by seeding suspicious query patterns in the source database workload in which the user attempts to access sensitive records that they would not usually touch. An alert is generated in the DTP system when there's unusual spikes in database queries as detected by AWS CloudWatch. The DTP system utilizes the behavioral model generated in SageMaker and realizes that the query pattern breaks away from the user's expected behavior. Thus, the DTP system automatically limits user's access privileges to limit further data exfiltration attempts due to this dynamics threat response. In the machine learning workload, unauthorized API activity is introduced to simulate the compromised account scenario. The attacker tries to inject the malicious data into the training dataset so that it modifies the training dataset and compromise the accuracy of the model afterward. Workload behavior analytics in the DTP system detects a sudden change in API usage pattern where the attacker attempts to upload a large volume of data far beyond the patterns of normal training schedules. This anomaly is reported as a possible attack and the DTP system automatically dries up API access to the workload to prevent further modifications.

In order to add additional security layers to the machine learning workload, the DTP system takes advantage of both AWS Identity and Access Management (IAM) and AWS Key Management Service (KMS), enforcing MFA and encrypting training data. It guarantees that if the attacker gets access to the dataset, they cannot alter it unless they also have the needed decryption keys.

During the whole course of this scenario, the DTP system continuously refines its own threat profile by running the workloads. For instance, once the insider threat is detected, the system refreshes the profile with the user's access pattern so future attempts to exfiltrate data by other insiders with common access credentials will be prevented. Also, the account profile for compromised account is updated with the attacker's ip address, geolocation and the usage pattern of their API to be able to block further requests proactively.

Real Time Analysis and Insights

The real time capabilities of the Dynamic Threat Profiling system are also shown in both scenarios in the experimental setup, in that it can detect, analyze, and respond to threats in cloud environments in real time. The DTP system utilizes AWS' scalable infrastructure and built in security components to take advantage of AWS' ability to dynamically adapt to emerging threats with minimal impact to the Cloud workloads.

Key to this experiment was real time data collection and the analysis of said data. In both cases, AWS services like CloudWatch, Security Hub, and Lambda were instrumental in real time collection and processing of data to enable real time responses of the DTP system to anomalies. The system was improved by additionally integrating workload behavior analytics and real-time threat intelligence to further compliment the system to detect sophisticated threats such as malware infection and insider threats that may go unnoticed by conventional secured solutions. Dynamic threat response is another key insight: As threats evolve, it needs to become automated. In particular, AWS provides serverless architecture that defines potential functions like Lambda, that allowed the DTP system to execute security policies (like patch management, rate limiting, and access revocation) and automatically had them executed without any human intervention. It not only made responses faster but also harmonized security measures executed on all workloads.

This experiment also showed the scalability of the DTP system as well. The DTP system shows how, by dispatching workloads across multiple regions, and by integrating with many different AWS services, it scales across large, complex cloud environments without compromising security. To accommodate organizations relying on cloud infrastructure to serve mission critical workloads, this scalability is critical.

Conclusion

Finally, this research paper sets out a broad study for enhancing cloud workload security via the proposed Dynamic Threat Profiling (DTP) methodology and threading together of real-time threat intelligence and workload behaviour analytics. Experimental validation of DTP to detect, profile, and mitigate complex threats in real time has been demonstrated using experiments on Amazon Web Services (AWS). DTP automates the act of responding to threats and integrates with existing security mechanisms, thereby greatly enhancing the resilience of cloud infrastructures against new types of threats. This work stresses the need for adaptive automated solutions for cloud security and establishes a basis for what is to come in multi-cloud and hybrid-cloud architectures.

This paper illustrates the potential use of Dynamic Threat Profiling (DTP) to protect the cloud environment from dynamic and evolving threats using the real time experimental setup described in this paper. The DTP system integrates real time threat intelligence, workload behavior analytics, and AWS scalable cloud infrastructure to deliver a powerful means to detect and mitigate threats in real time. This experiment illustrates, via two separate scenarios (one on real time threat intelligence and the other on workload behavior analytics), how DTP can mitigate a wide variety of cyber threats such as malware infections, DDoS attacks, insider threats and compromised accounts.

As cloud adoption keeps up its pace, the demand for such adaptive and intelligent security frameworks, such as DTP, will also rise. These results allow us to understand how DTP can be applied in realistic cloud environments, in a scalable, automated, and proactive fashion for cloud security.

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