Athena: A Framework for Scalable Anomaly Detection in Software-Defined Networks

Seunghyeon Lee†, Jinwoo Kim†, Seungwon Shin‡, Phillip Porras‡, and Vinod Yegneswaran†
†KAIST  ‡SRI International
{seunghyeon, jinwoo.kim, claude}@kaist.ac.kr, and {porras, vinod}@csl.sri.com

Abstract—Network-based anomaly detection is a well-mined area of research, with many projects that have produced algorithms to detect suspicious and anomalous activities at strategic points in a network. In this paper, we examine how to integrate an anomaly detection development framework into existing software-defined network (SDN) infrastructures to support sophisticated anomaly detection services across the entire network data plane, not just at network egress boundaries. We present Athena as a new SDN-based software solution that exports a well-structured development interface and provides general purpose functions for rapidly synthesizing a wide range of anomaly detection services and network monitoring functions with minimal programming effort. Athena is a fully distributed application hosting architecture, enabling a unique degree of scalability from prior SDN security monitoring and analysis projects. We discuss example use-case scenarios with Athena’s development libraries, and evaluate system performance with respect to usability, scalability, and overhead in real world environments.

I. INTRODUCTION

Tracking and responding to network traffic anomalies is an ubiquitous and significant challenge faced by all network operators [1]. Sudden and massive deviations in the volume and mix of data flowing through the network infrastructure, due to congestion, outages, network probes, and flooding attacks, are so frequent that few networks would fail to benefit from integrated network anomaly detection services. Even anomalies that arise from benignly-motivated incidents, such as flash crowds, may threaten the ability an enterprise to maintain reliable network operations.

Software-Defined Networking (SDN) offers the potential to explore new efficient strategies for instrumenting networks, integrating software detection services, and responding to anomalies that would otherwise impede network operations. For example, by leveraging the centralized control plane to track new flow requests and extracting data plane statistics, one can analyze live network data flows without requiring the insertion of third-party devices (e.g., a network monitoring middlebox). Indeed, a survey of recent research proposals illustrates the increasing exploration of SDN strategies to integrate network misuse and anomaly detection services [2], [3], [4], [5], [6], [7], [8], [9], [10].

However, while these proposals offer a diverse exploration of SDN-based monitoring strategies, several significant technical challenges remain. First, most SDN-based threat monitoring proposals that implement monitoring services as SDN applications, do not consider the issue of network-wide large-scale data extraction and management across a distributed data plane, with many switches and controller instances. Second, prior research has primarily focused on applications designed for specific suspicious or anomalous activity. Prior SDN monitoring projects have employed focused subsets of features from SDNs for tracking specific phenomena rather than defining a feature framework for building SDN-enabled network anomaly detection services. Third, there is limited research on network features and anomaly detection algorithms for activities that cross the control and data plane boundaries.

We present a scalable framework, called Athena, for constructing network monitoring services in large-SDN deployments, and providing flexible third-party development of new detection models. Athena exports an API that provides a well-structured development environment for implementing a wide range network anomaly detection applications across a large physically distributed SDN control and data plane. Athena’s API offers developers an abstraction from a complex data extraction service, reducing the programming effort required to implement and deploy new anomaly detection services. In contrast to existing work, Athena includes a wide range of network features and detection algorithms for use in simplifying the design and deployment of general-purpose network data plane anomaly detection applications in large-scale SDN networks. In fact, other than its requirement for OpenFlow support, the framework avoids the need for specialized hardware, thereby dramatically minimizing the need to modify an SDN stack when introducing new anomaly detection services.

To address the issue of scalability across large distributed SDN deployments, Athena’s network feature collection and data management framework employs a distributed database, a computing cluster, and a distributed controller. It collects and generates network features above the SDN controller instances in a distributed manner, and publishes the network features to a distributed database. To accelerate runtime detection model generation, Athena incorporates a machine learning (ML) library from which anomaly detection algorithms may be implemented and then deployed as jobs across Athena’s computing cluster. Athena exports high-level APIs that allow operators to design and deploy anomaly detection applications with a minimum of programming effort. This approach both reduces the total computation time necessary to perform anomaly detection, while increasing the scalability of data management services on which these algorithms are run.

The key contributions presented in our paper include the following:

- Introduction of Athena as a new anomaly detection application development framework that leverages SDN functionality to explicitly support ML-based network anomaly...
Permission type: all
Copyright year: 2023
Publisher: IEEE
Doi: 10.1109/ACCESS.2023.3265881

II. FIVE CONSIDERATIONS IN DESIGNING SCALABLE SDN ANOMALY DETECTION SERVICES

The design and integration of network anomaly detection services in traditional networks have been well studied [12]. We understand how to integrate hardware elements to extract network traffic features at strategic network points, how to apply a wide range of analytics to these features, and how to correlate relevant reports to effect a network’s security posture. However, SDNs offer a departure from these strategies by providing new methods for dynamic instantiation of monitoring services with a global view of the network topology that is continuously updated.

The design goals for the Athena anomaly detection framework for SDNs include the following: 1) provide for an extensive feature extraction infrastructure without hardware device integration, 2) abstract data acquisition and simply anomaly detection service implementation, and 3) simplify large-scale deployment of monitoring services without modification to the SDN infrastructure itself. This section discusses several key choices and considerations toward addressing these goals.

1) Centralized Management Perspective: We illustrate the two management design paradigms, legacy versus SDN, in Figure 1. While SDN’s support centralized network-wide monitoring, developers are burdened with the requirement to implement a centralized controller that monitors and manages the network with a global network view. Furthermore, each device may export a wide menagerie of network features (e.g., logs, statistics, and alerts) forcing the developer to perform post-processing to normalize network features using approaches like VAST [13].

2) Network Feature Quality and Accessibility: The selection and accessibility of legitimate network features for real-time monitoring is an essential task when designing any network monitoring framework, particularly frameworks that are intended to facilitate off-the-shelf sharing of anomaly detection algorithms. Athena directly addresses these needs for feature quality and accessibility, by providing (i) normalized network-feature access and libraries from which a wide range of ML-based detection algorithms may be designed and deployed across large-scale distributed SDNs, and (ii) dynamic threat mitigation APIs that can be launched in response to perceived threats to the SDN. We will leverage example use cases to address well-known anomaly detection problems, and demonstrate the utility of the Athena framework by applying it to detect a novel SDN-specific anomaly (Section V).

3) Monitoring Networks with Highly Dynamic Topologies: Enterprise networks continue to become more complex, more virtual, and dynamic to meet an increasingly diverse set of operational requirements. Traditional security and network devices are often integrated at physically strategic points in the network, and it is the burden of the operator to manage and adjust their integration and configuration as the network topology changes. Since Athena is built into the SDN control layer, applications built over this framework can automatically extend monitoring and anomaly detection capabilities to dynamic network topologies.

4) Flexible Scale-up and Scale-out of the Anomaly Detection Framework: Large network environments imply increased event volumes, larger sets of distributed switches within the data plane, and complex network operating requirements that increase the complexity of both the control plane and the hosted network applications. A key challenge for Athena is to introduce a network monitoring framework that will enable anomaly detection applications to scale in speed, to offer distributed computation, and to provide data management APIs.
that enable high volume event processing. To date, several network monitoring projects have pursued scalability among their design requirements, such as [14], [15], [16], [17], [18], [7], [3], [2], [19], [20], [5]. However, most of these efforts (with the exception of [17]) focus on uncontrolled environments and none of them provide explicit support for anomaly detection algorithms. In contrast, Athena is designed as a fully-distributed event collection and processing framework with scalable feature collection and management to support anomaly detection.

5) Coding Efficiency for Anomaly Detection Algorithm Development: While SDN controller APIs [21], [22], [23], [24], [14] enable a wide range of network applications that have been implemented and shared, these APIs are largely insufficient to support network anomaly detection applications. This absence of a generalized network monitor development framework for SDNs contributes to slower progress in the design and deployment of SDN security applications. To overcome this issue, Athena exports high-level APIs that support the extraction of critical features, management of data streams, and detection of anomalous network behaviors.

III. ATHENA DESIGN

Athena is a fully-distributed network anomaly detection framework, in which an Athena instance is hosted above each distributed SDN controller, such as with ONOS instances deployed across a wide area network. For example, Figure 2 illustrates three Athena instances that are distributed across three SDN controllers. Each Athena instance monitors the network behavior that is associated with its hosted network controllers and the data plane hosted by the controllers.

As shown in Figure 2, conceptually, Athena incorporates the Feature Generator, which collects SDN control messages issued by the local control and data plane, generates network features, and publishes features to a distributed database (a DB cluster) for feature management. The Attack Detector detects potential network problems using the developer-defined detection algorithm. The Attack Reactor has responsibility for mitigating detected threats by issuing mitigation actions to the data plane. Operators need not modify their existing SDN stack to host Athena, as its inputs are SDN control messages, along with small code stubs within the controller. We discuss the details of Athena’s architecture in Section III-A.

Above the framework, Athena provides the set of components that compose its user-friendly development environment. Athena exports a high-level API called as the Athena NB API, which allows developers to create anomaly detection applications in a manner that is agnostic to the underlying SDN implementation. Athena offers an abstraction to the controller and data plane implementations and versions, enabling rapid prototyping and minimizing deployment costs.

Athena provides 8 core and 70 utility APIs, described in Table II. Developers implement anomaly detection tasks as Athena apps (shown in Figure 2), using the Athena Northbound API (NB API). These applications generate anomaly detection models, perform real-time detection, and implement live threat responses.

A. Athena System Design

Figure 3 illustrates the three major elements of the Athena framework: the southbound element, the distributed DB and computing clusters, and the northbound element. The southbound element monitors the network behaviors including the control plane, extracts features from the SDN control messages, implements live detection algorithms, and invokes mitigation reaction. The northbound element exports high-level APIs to enable analysis applications to perform anomaly detection tasks, including network monitoring. The third major element is composed of a distributed database cluster that provides network-wide feature access, and a computing cluster for running distributed parallel instances of Athena applications.

1) The Athena Southbound (SB) Element: The Southbound element’s main purpose is to isolate control messages, extract features to drive the analysis algorithms, and mitigate detected problems. However, these tasks must be performed across several parallel controller instances and many physically distributed switches. Athena achieves this scale by employing SB instances that operate separately on each controller. Further, it uses distributed 3rd party applications to provide parallel data processing environments. Each instance is responsible for monitoring its associated controller and those switches that the controller directly manages, then provides detection algorithms and reaction strategies. The Athena SB element consists of four major sub-components:

1A) SB Interface: The main role of the SB Interface is to monitor (selected) SDN control messages issued by both the data plane and the control plane, and to deliver network management commands issued by the Attack Reactor (e.g., issuing flow rules) through the Athena Proxy. The proxy is a small code snippet instantiated at each controller instance. Athena leverages proxy-stubs that work like general network applications to avoid consistency issues that might arise from issuing control messages to the data plane without involving the controller. When the Athena Proxy issues flow rules to the data plane, the controller automatically updates its internal status according to the issued flow rules.
TABLE I. AN ENUMERATION OF Athena FEATURE TYPES.

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Protocol-centric</td>
<td>Features derived from SDN control messages directly.</td>
<td>Volume (Packet counts, byte counts)</td>
</tr>
<tr>
<td>Combination</td>
<td>Combined features derived from Protocol-centric by pre-defined formula.</td>
<td>Flow utilization (Packets / Duration)</td>
</tr>
<tr>
<td>Stateful</td>
<td>Stateful features according to the network states.</td>
<td>Pair flow ratio (Pair flows / Total flows)</td>
</tr>
</tbody>
</table>

![Athena Architecture Diagram]

**Fig. 3.** An overview of the Athena system architectural components. The Athena framework is composed of the extensible southbound element, the unified northbound element, and the Athena application instantiation layer.

1B) Feature Generator: The Feature Generator examines incoming control messages to derive Athena features, which we enumerate in Table I, and the internal status of control plane to extract important behavioral features from the control plane (e.g., tracking flow origins). The Feature Generator maintains hash tables to track the status of the previous features for generating Variation and network status for maintaining message State. The Feature Generator includes a garbage collector to periodically remove outdated entries. It also attaches additional meta information (e.g., timestamp). We discuss the details of Athena features in Section III-A3.

1C) Attack Detector: The Attack Detector uses detection algorithms to find potential network threats. The detector generates detection models according to requests from the Detector Manager in the Athena NB, and analyzes generated features from the Feature Generator. It is designed to operate live or in batch mode. When it receives a request related to one or more tasks, it translates the request to functions and performs jobs with a single and a distributed manner according to the type of job. For example, while in learning mode, the Attack Detector distributes jobs to the computing cluster to provide a scalable analysis environment. For a small dataset, it handles the request on a single instance to reduce communication overhead.

1D) Attack Reactor: The Attack Reactor enforces mitigation strategies to the data plane. When it receives mitigation strategies from the Detector Manager, it translates requests to network management messages to be sent to the data plane through the Athena Proxy.

2) The Athena Northbound (NB) Element: The Athena Northbound element exports Northbound APIs, which allow application developers to utilize Athena’s functionalities for an anomaly detection, providing scalability as well as SDN implementation transparency. We describe below the five major sub-components of the NB element.

2A) Feature Management Manager: The Feature Manager provides a unified mechanism that applications use to retrieve and receive network features according to user-defined constraints. It receives feature requests from each application and translates them into queries that it issues to the Athena distributed database. It transfers requested data from the distributed database to the computing cluster managed by the Detector Manager, reducing data transmission overhead while transferring large-scale datasets. It maintains an event delivery table, which maintains a set of application constraints, that is triggered when incoming network features match the constraints. When processing real-time incoming features from the Athena SB, it forwards the features to both the Athena applications and the Detector Manager.

2B) Detector Manager: The Detector Manager provides a wide-range of well-known ML algorithms to generate detection models including a simple threshold-based detection algorithm. It also validates large-scale network features. It works with the Feature Manager to dynamically validate incoming network features and provides unified APIs that allow operators to perform detection tasks with transparency to details of the algorithms. For example, when running a K-Means algorithm in the clustering category with the Decision Tree algorithm in the classification category, the operator will use the same APIs in Table II. An operator does not have to consider the characteristics of each ML type, since the Detector Manager automatically configures ML parameters according to requests of ML types by operators (e.g., labeling features).

2C) Reaction Manager: The Reaction Manager provides mitigation strategies that allow the Athena applications and operators to enforce mitigation actions by issuing flow rules to the data plane. The applications enforce pre-defined course-of-actions to handle network problems, independently from the underlying network controller, by issuing requests to the SB Attack Reactor, which are automatically translated to flow rules.

2D) Resource Manager: The Resource Manager exports functions to manage resources related to feature collection. It dynamically adjusts the number of monitored network entities and generated network features, according to requests from Athena applications. This allows Athena applications to control monitoring fidelity based on dynamic network conditions.

2E) UI Manager: The UI Manager services an interface, that displays Athena application’s results and provides an interaction mechanism.

3) Athena Off-The-Shelf Strategies: As an anomaly detection framework, Athena provides a set of off-the-shelf strategies including network features, detection algorithms, and reactions.
3A) Athena Features: In total, Athena exposes over 100 network monitoring features to the NB API. The full list of network features is available at SDNSecurity.org [11]. The types of features are enumerated in Table I. Protocol-centric features are directly derived from OpenFlow control messages, such as packet count from flow statistics. Combination features refer to combined features derived from pre-defined formulas, such as the features in [10], and include more meaningful information regarding SDN-specific features. For example, Flow Utilization represents how much traffic a flow delivers to its associated output port. The Stateful field represents the features including states of indicator operations. For example, Pair Flow Ratio represents how many flows manifest active two-way connection between a sender and a receiver.

Athena’s feature format is illustrated in Figure 4. The feature format consists of the index fields and the feature fields. The index fields include the Index, which contains information about feature’s origins (e.g., Switch ID, port ID) including indicators (e.g., OpenFlow match fields), and Meta Data that represents additional information such as a timestamp and semantics of the control plane associated with the feature (e.g., Flow origins). The feature fields are appended after the index fields to represent an actual behavior of the network.

3B) Athena Detection Algorithms: Athena provides a set of detection algorithms that allow its applications to find potential network threats and problems. The algorithms include five categories, which are described in Table IV. Currently, Athena supports 11 machine learning algorithms hosted on a computing cluster to perform scalable analyses.

3C) Athena Reactions: Athena Reactions manage the data plane according to changes of the network status. After detecting a network threat, the applications hosted by Athena may choose to invoke a mitigation strategy. Athena currently supports two types of mitigation actions: Block, which blocks certain hosts; and Quarantine, which isolates suspicious hosts to user-defined destinations.

IV. THE ATHENA DEVELOPMENT ENVIRONMENT

The Athena development environment (DE) exports a set of high-level APIs that allow operators to design and implement a scalable network anomaly detector in a manner that abstracts both the SDN version dependencies and infrastructure-specific configuration details. Here we discuss Athena’s northbound APIs and outline the steps involved in implementing various anomaly detection services.

A. Athena Northbound API

The Northbound (NB) API is configuration-based. Developers use it by configuring parameters to execute anomaly detection tasks. For example, one can generate a detection model by defining a set of 1) detection parameters, such as “TCP_PORT==80 && time==1 day”; 2) detection features, such as “sampling (20%), default normalization”; and 3) a preferred detection algorithm, such as “K-means, k==5”.

Athena currently supports eight core functions described in Table II, and several pre-defined parameters, described in Table III. RequestFeatures is a monitoring API that retrieves desired Athena features using the query interface. For example, a developer may create a query that requests “flow utilization per network application”, “unstable ports during a 1-day temporal window” and “top 10 congested links”. Athena currently supports the query operators described in Table IV. The ManageMonitor API uses queries to turn monitoring on/off for specific network features.

As a detection-related API, we provide the GenerateDetectionModel for creating detection models, and ValidateFeatures for large-scale feature validation. The APIs commonly receive a query to retrieve a desired feature set, and apply the Preprocessor, which transforms the features before use. GenerateDetectionModel defines a detection algorithm with its parameters (e.g., K of the K-Means algorithm), and generates a detection model. The model is used by ValidateFeatures to validate target features, and it produces results that summarize the validation task. Athena generates a detection model during the learning phase when a machine-learning (ML) algorithm is employed, and exports a pre-defined model without a learning phase when using other algorithms (e.g., threshold-based detection). Table IV describes the supported functions of the Preprocessor and ML algorithms.

Athena provides APIs that allow an application to handle network features in an online manner. First, AddEventHandler enables analysis applications to receive Athena features dynamically. Applications register an event handler with a user-defined query. The manager then dynamically evaluates whether an incoming feature satisfies the query, and if so it forwards the feature to the applications. For example, an application may pass the query “IP_DST==server address && Port==80”. The event handler is also used for live validation by AddOnlineValidator. This allows an operator to define an operational mode for specific anomaly detection tasks (e.g., A stand-alone mode, and a distributed mode). ShowResults represents the results as a visualized graph, providing operators with direct insight to Athena’s results. The Reactor enforces mitigation strategies to the data plane according to requests of the application with queries, such as “IP_SRC in {suspicious hosts}” and invokes response functions described in Table IV.

B. Athena Application

Figure 5 illustrates the steps involved in designing and implementing an anomaly detector. Developers select off-the-shelf strategies (e.g., network features, detection algorithms, and reactions) to perform anomaly detection tasks. Based on these selections, they use supported NB APIs to construct a consolidated anomaly detector, including the selected network feature generation, model creation with fine-grained filtered
network features, feature validation with a large-scale dataset, run-time threat detection logic, a dynamic threat mitigation policy, and results from GUI/CLI generation.

Athena automatically performs the anomaly detection task, including task integration with the external DB cluster and computing cluster. It reports (intermediate) results to the application while performing anomaly detection. The application updates internal status and configures new Athena hosted anomaly tasks based on the results. Furthermore, Athena provides a GUI/CLI interface that allows the operator to receive alerts and manage the Athena application in a centralized manner.

V. ATHENA USE CASES

To illustrate the utility of the Athena framework, we present multiple sample anomaly detection applications. Due to space limitations, we only show the pseudocode for the DDoS Detector (scenario #1).

A. Scenario 1: A Large-scale DDoS Attack Detector

One strength of the Athena framework is its ability to create scalable network anomaly detection services across large and physically distributed network environments. To demonstrate this scalability, we implement a large-network DDoS attack detection application using Athena’s northbound APIs. Since Athena automatically collects all of the network features across the SDN data plane by default, an operator may deploy Athena on the network to automatically gather the features necessary to drive our detector. Here, we discuss DDoS model creation, feature validation, and summarize our test results.

Creating the DDoS Detection Model: Detection model creation begins with a definition of the desired network features for use during the training phase. The developer sets

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RequestFeatures(q)</td>
<td>Request a set of Athena features with user-defined constraints including feature re-organization.</td>
</tr>
<tr>
<td>ManageMonitor(q, o)</td>
<td>Turn on/off a network monitoring including a feature generation.</td>
</tr>
<tr>
<td>GenerateDetectionModel(q, f, a)</td>
<td>Generate an anomaly detection model according to an user-defined algorithm and features.</td>
</tr>
<tr>
<td>ValidateFeatures(q, f, m)</td>
<td>Validate a set of Athena features with a generated detection model.</td>
</tr>
<tr>
<td>AddEventHandler(q)</td>
<td>Register an event handler to retrieve features from Athena according to user-defined constraints.</td>
</tr>
<tr>
<td>AddOnlineValidator(f, m, e)</td>
<td>Register an online validator to examine an incoming feature in an online manner.</td>
</tr>
<tr>
<td>Reactor(q, r)</td>
<td>Enforce an action to the data plane.</td>
</tr>
<tr>
<td>ShowResults(α)</td>
<td>Display the results from Athena with a graphical interface.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Query (q)</td>
<td>Unified query to retrieve Athena features with constraints.</td>
</tr>
<tr>
<td>Preprocessor (f)</td>
<td>Preprocessing statement to re-design features.</td>
</tr>
<tr>
<td>Algorithm (a)</td>
<td>Description of an algorithm including parameters of the algorithm.</td>
</tr>
<tr>
<td>Model (m)</td>
<td>Generated detection model.</td>
</tr>
<tr>
<td>Results (r')</td>
<td>Results of a validation or a feature request.</td>
</tr>
<tr>
<td>Event handler (e)</td>
<td>Event handler to receive online Athena events.</td>
</tr>
<tr>
<td>Reactions (r)</td>
<td>Reactions for handling suspicious hosts.</td>
</tr>
<tr>
<td>Operations (o)</td>
<td>Flags for a network monitoring per features.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Arithmetic</td>
<td>&gt;, &gt;=, =, /=, &lt;=, &lt;</td>
</tr>
<tr>
<td>Relationship</td>
<td>and, or</td>
</tr>
<tr>
<td>Options</td>
<td>Sorting, Aggregation, Limiting</td>
</tr>
<tr>
<td>Preprocessor (f)</td>
<td>Description</td>
</tr>
<tr>
<td>Weighting</td>
<td>Emphasize certain features</td>
</tr>
<tr>
<td>Sampling</td>
<td>Select a subset from entire features</td>
</tr>
<tr>
<td>Normalization</td>
<td>Standardize the range of independent variables</td>
</tr>
<tr>
<td>Marking</td>
<td>Mark a set of entry labeled as malicious entry</td>
</tr>
<tr>
<td>Algorithm (a)</td>
<td>Supported algorithms</td>
</tr>
<tr>
<td>Boosting</td>
<td>Gradient Boosted Tree</td>
</tr>
<tr>
<td>Classification</td>
<td>Decision Tree, Logistic Regression, Naive Bayes, Random Forest, SVM</td>
</tr>
<tr>
<td>Clustering</td>
<td>Gaussian Mixture, K-Means</td>
</tr>
<tr>
<td>Regression</td>
<td>Lasso, Linear, Ridge</td>
</tr>
<tr>
<td>Simple</td>
<td>Threshold</td>
</tr>
<tr>
<td>Reactions (r)</td>
<td>Description</td>
</tr>
<tr>
<td>Block</td>
<td>Block target hosts</td>
</tr>
<tr>
<td>Quarantine</td>
<td>Isolate hosts in honeynets</td>
</tr>
<tr>
<td>Operations (o)</td>
<td>Description</td>
</tr>
<tr>
<td>True</td>
<td>Turn on network monitoring</td>
</tr>
<tr>
<td>False</td>
<td>Turn off network monitoring</td>
</tr>
</tbody>
</table>

Athena automatically performs the anomaly detection task, including task integration with the external DB cluster and computing cluster. It reports (intermediate) results to the application while performing anomaly detection. The application updates internal status and configures new Athena hosted anomaly tasks based on the results. Furthermore, Athena provides a GUI/CLI interface that allows the operator to receive alerts and manage the Athena application in a centralized manner.
Application 1: A pseudo-code illustration of an Athena-based DDoS attack detection application.

```c
/* Define the features to be trained */
q_train = GenerateQuery (constraints of features);

/* Define data pre-processing */
f = GeneratePreprocessor (Normalization,
Weight for certain features,
Marking malicious entries, ...
);

/* Register the features used in the algorithm */
f.addAll(candidate features);

/* Define an algorithm with parameters */
a = GenerateAlgorithm (a detection algorithm);

/* Generate a detection model */
m = GenerateDetectionModel (q_train, f, a);

/* Define the features to be tested */
q_test = GenerateQuery (constraints of features);

/* Test the features */
r' = ValidateFeatures(q_test, f, m);

/* Show results with CLI interface */
ShowResults(r');
```

**TABLE VI. A COMPARISON OF THE TEST ENVIRONMENT.**

<table>
<thead>
<tr>
<th>Category</th>
<th>[10]</th>
<th>Athena</th>
</tr>
</thead>
<tbody>
<tr>
<td>Switch</td>
<td>3 OF switches</td>
<td>18 OF switches (6 physical, 12 OVS)</td>
</tr>
<tr>
<td></td>
<td>3 links</td>
<td>48 links</td>
</tr>
<tr>
<td>Link</td>
<td>1 instance</td>
<td>3 instances</td>
</tr>
<tr>
<td>Controller</td>
<td>Feature</td>
<td>Algorithm</td>
</tr>
<tr>
<td></td>
<td>6-tuples</td>
<td>SOM</td>
</tr>
<tr>
<td></td>
<td>10-tuples</td>
<td>K-Means</td>
</tr>
</tbody>
</table>

the data preprocessing parameters to normalize the features that capture the characteristics of a DDoS attack described in Table V. These features are set by the `f.addAll()` utility API. Here, we configure Weight for emphasizing certain network features, and Marking for annotating malicious entries.

Algorithm represents a detection model, and it is configured with a machine learning algorithm and its parameters (e.g., we may choose K-Means with k = 5, and 20 iterations). Developers then invoke `GenerateDetectionModel` to create the detection model, and `Athena` distributes the ML detection tasks to compute worker nodes. After job completion, the application receives the detection model. These steps are outlined in the pseudocode.

**DDoS Feature Validation:** The developer next defines the desired network features to receive results from an analysis of the testing phase. The developer defines Query and Preprocessor in the same way, and calls `ValidateFeatures` with the pre-defined Query, Preprocessor, and the Model. Upon completion of the testing phase, `Athena` generates a testing summary, as illustrated in Figure 6.

**DDoS Testing Environments and Results** We established a testing environment to reflect an enterprise-scale network topology as illustrated in Figure 7, and compare our environment with previous work for an SDN-based DDoS detection [10], as described in Table VI. Our topology consists of 48 links and 18 switches (6 physical switches, and 12 OVS switches) managed by three distributed network controllers, including `Athena` instances. We deployed a K-Means-based algorithm with 10 tuples, and simulated the testing environment using a Mininet environment. The attack scenario is similar to traffic patterns in [10]. The detection rate is 99.23%, and false alarm rate is 4.46%. We will discuss these results further in Section VII-B.

**B. Scenario 2: Link Flooding Attacks (LFA) Mitigation**

LFA represents a serious and common network attack, in which the adversary saturates a target network area with few resources [25]. A noteworthy aspect of the `Athena` framework is that, unlike some other tools, it produces monitoring applications that are deployable without modification to the underlying network infrastructure. For example, we compare the implementation of LFA mitigation using `Athena` with Spiffy [26], which utilizes the transmission rate control mechanism within the TCP protocol to detect and mitigate LFA. Spiffy adjusts how much traffic should be delivered through a conditional assessment of the current network status. It assumes that malicious flows do not respond to a temporary change of network status, which differs from the normal profile of legitimate flows. As a solution, temporary bandwidth expansion (i.e., expanding bandwidth temporarily to detect malicious flows by leveraging characteristics of TCP) and runtime flow migration (i.e., re-assigning flows to expand bandwidth for a suspicious link) are proposed.
LFA Mitigation Service using Athena: We have implemented a comparable Link Flooding Attacks mitigation service as an Athena application. In Table VII, we present a comparison of the Spiffy implementation of the LFA mitigation service using the same solution implemented with the Athena framework. Here, the demanding functions involved in LFA detection and mitigation include solving link congestion detection, recognizing per-flow rate changes, and implementing flow alterations.

LFA Event Handler Registration: The LFA detector receives link usage to measure link utilization and per-flow changes to distinguish attackers. Since Athena provides various volume-based features including per-flow changes, we define these candidate features, including a threshold. For example, the candidate features are volume-based features such as `port_rx_bytes_var`, which represents changes at each port, and `flow_byte_count_var`, which represents the change in byte counts. Likewise, we choose volume-based features (e.g., `port_rx_bytes`). Finally, we simply call the `AddEventHandler` API with a pre-defined event handler to perform the detection and mitigation of incoming events.

LFA Detection Logic: Developers may implement the custom detection logic in the Event_Handler. The detection logic includes lightweight threshold-based flooding detection, which measures volume per port, and may use a TBE-based detector that tracks per-flow changes. Lastly, the mitigation logic simply blocks suspicious hosts based on the detection results by invoking Reactor.

Using Athena, we can implement the proposed Spiffy LFA detection and mitigation mechanism with our SDN test environment in under 25 lines of Java code, excluding the custom detection logic.

Comparing Athena-based LFA mitigation with Spiffy: Table VII shows the comparison of LFA detection and mitigation using Spiffy and Athena. Spiffy uses an SNMP-based link utilization measurement to detect congested links. However, operators need to configure SNMP-based measurement functions, and the network’s switches must also support this function. Spiffy leverages OpenSketch-enabled switches [4] to detect rate changes from an edge. Although OpenSketch could reduce overhead to measure rate changes, operators must deploy OpenSketch-enabled switches into their existing network infrastructure. This increases the deployment cost of the Spiffy solution, as it requires features that are non-standard in many SDN environments. Implementing the same anomaly detection algorithm using Athena removes the need for vendor-specific network devices and SNMP-enhanced monitoring capabilities. In contrast to the Spiffy environment, Athena’s application can operate directly on the SDN without data plane alterations.

C. Scenario 3: Network Application Effectiveness (NAE)

Network applications are critical elements of a network’s SDN stack, as they embody the logic that defines the flow policies for the entire network. Thus, validating application behavior is important, particularly before their adoption into critical or sensitive network environments. Unfortunately, it is difficult to verify application behavior, as modern SDN environments may allow multiple applications to run on a controller in parallel. These applications can also cause conflicts in the form of flow rule contradictions. Several SDN researchers have tried to solve this problem through control mechanisms to resolve network application conflicts [27], [28], [29], [30]. However, they did not explore misuse anomalies that can violate network policies defined at deployment. We refer to this as the Network Application Effectiveness (NAE) problem, as illustrated in Figure 8.

Let us assume that an operator installs a load-balancing (LB) application, which defines flow rules intended to evenly distribute a target traffic load across a given set of network services. Consider a security application that attempts to direct FTP-related traffic through an inline security device that analyzes the FTP traffic for signs of malicious command patterns. In this scenario, the LB app and the security app may conflict in their decisions regarding packet forwarding. To handle conflicts, operators set a higher priority for the security app, thus allowing it to over-rule the LB app when their rules conflict. While the problem is well known and addressed by prior work [27], [28], [29], [30], these projects do not consider how to detect the wide range of unwanted network anomalies that may arise as flow rules are evaluated and discarded by the control layer.

The above scenario leads to interesting potential flow pattern anomalies that can arise as the control plane begins to resolve conflicts in the rules produced by the competing applications. For example, if the primary purpose of the network in Figure 8 is to serve FTP users, the network may suffer significant overhead by the unbalanced load produced by the security policy. When the network is dominated by FTP flows, this traffic will begin to saturate S6 due to the security app. Although S3 is available to deliver traffic to the destination, it cannot receive traffic due to the security app’s shortest path policy which dictates that all traffic from S6 goes to S7. To evaluate this, we set up an experimental environment, with the edge switches S1 and S5, where each host downloads files or accesses pages from the FTP and web hosts.
servers respectively.

**NAE Monitor Implementation:** Detecting the NAE problem is straightforward with *Athena* since it provides a strong query mechanism to retrieve network features with advanced data preprocessing capabilities (e.g., sorting, aggregation, and ranking). We register an event handler to retrieve flow-related network features per application by `AddEventHandler(networkFeaturesPerApplication)`. We register an event handler to retrieve flow-related data preprocessing capabilities (e.g., sorting, aggregation, and query mechanism to retrieve network features with advanced

**Athena** is an emerging SDN distributed controller for large-scale networks, focusing on service provider use-cases. *Athena* is an emerging SDN distributed controller for large-scale networks, focusing on service provider use-cases. We have developed a prototype implementation of the **NAE Monitor Implementation:** Detecting the NAE problem is straightforward with *Athena* since it provides a strong query mechanism to retrieve network features with advanced data preprocessing capabilities (e.g., sorting, aggregation, and ranking). We register an event handler to retrieve flow-related network features per application by `AddEventHandler(networkFeaturesPerApplication)`, and analyze whether a given feature obeys a user-defined SLA (service level agreement) \(^3\) by the `Check_SLA()` \(^4\). If an incoming event obeys the SLA, the `ResultsGenerator` utility API is invoked to generate the `Results` to notify operators. Finally, it reports anomalous behavior to the operator’s GUI interface via the `ShowResults` API, as illustrated in Figure 9.

**NAE Analysis Results:** Figure 9 shows our application results. Since we set up a query with “Match DPID=={6 or 3}”, the results only represent relevant features aggregated by app ID, switch ID, and timestamp. It shows a global view of packet count information per switch. The sawtooth pattern in this graph is caused by the expiration of flow rules, since LB app issues flow rules with *soft timeout* \(^5\). After the security app is activated from 03:58, the security app takes over most traffic flows, re-routing their packets into the path of the security device. Therefore, the LB App loses forwarding control due to its low priority. Although the LB app is active, the network begins to suffer unexpected saturation in some links and low volume in others. We implemented the NAE problem detector on *Athena* within 30 lines of Java code.

VI. IMPLEMENTATION

We have developed a prototype implementation of the *Athena* framework that integrates within ONOS \([14]\), which is an emerging SDN distributed controller for large-scale networks, focusing on service provider use-cases. *Athena* also employs MongoDB \([31]\) for its distributed database, Spark \([32]\), \([33]\) for its scalable computing cluster, and JfreeChart \([34]\) for the graphical interface. The prototype operates on ONOS version 1.6, using OpenFlow 1.0 and 1.3, MongoDB version 3.2, Spark version 1.6, and JfreeChart version 1.0.13. We have implemented the prototype of *Athena* with approximately 15,000 lines of Java code.

*Athena* is implemented as an ONOS subsystem, which provides services to an application layer. We modify the implementation of OpenFlowController to get OpenFlow control messages directly, and OpenFlowDeviceProvider to issue statistics request messages to the SDN data plane. We mark an XID value for statistics request messages to calculate variation features exactly, as ONOS issues request messages to the data plane as part of its management functions. To extract application information per flows, *Athena* leverages the FlowRule subsystem, which manages flow entries within the controller. The *Athena* application operates as a separate process and communicates with the *Athena* framework via interprocess communication to reduce dependencies.

VII. EVALUATION

We now evaluate *Athena* with respect to its usability, network scalability, and overhead. To explore its usability, we consider the design of *Athena*’s anomaly detection applications against comparable applications developed without *Athena*. For the scalability assessment, we evaluate performance of the large-scale DDoS anomaly detection algorithm introduced in Section V-A. Finally, we measure the overhead of *Athena* feature extraction using the Cbench benchmark. To evaluate our work, we created an experimental environment with five high performance servers (four Intel hexa-core Xeon E5-1650, one Intel octa-core Xeon E5-2650) with 64GB RAM, two Intel I5 quad-core I5-4690 and 16GB RAM memory, seven physical switches \(^6\).

A. Evaluating Usability of *Athena*

<table>
<thead>
<tr>
<th>DDoS detector (Algorithm)</th>
<th>Athena</th>
<th>Spark</th>
<th>Hama [35]</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-Means</td>
<td>45</td>
<td>825</td>
<td>817</td>
</tr>
<tr>
<td>Logistic Regression</td>
<td>42</td>
<td>851</td>
<td>829</td>
</tr>
</tbody>
</table>

In evaluating the usability of *Athena*, we implemented a DDoS detection application within different environments, and then provide a rough approximation of the implementation complexity by quantifying the source lines of code (SLoC) required to implement the application. While imperfect, SLoC is often used as a metric of usability (e.g., \([36]\), \([37]\)). We believe that SLoC (application compactness), given the lack of a large developer-base for feedback, provides a useful early usability measure, similar in spirit to how it was applied to answer this same question in related prior work.

Each resulting application embodies the functionality of the DDoS attack detector in Section V. As summarized in Table VIII, the application based on *Athena* uses 5% of the lines of code that comparable functionalities require when implemented on Spark \([32]\) and Hama \([35]\).

\(^3\)In this scenario, the SLA is that traffic should be distributed evenly per switch.

\(^4\)This function is a custom algorithm to detect asymmetric traffic patterns.

\(^5\)The soft timeout is used for deleting flow rules, when there are no incoming packets within a certain time.

\(^6\)Two Pica8 P3290, two Pica8 P3297, two Pica8 AS4610, and one ARISTA 7050T-36.
B. Measuring Scalability of Athena

Figure 10 presents the performance results for the DDoS detection application in Section V-A. We use an experimental environment with ten instances on the three Xeon servers. The instances consist of six compute nodes and a master node on the two hexa-core Xeon servers, and three DB nodes on the octa-core Xeon server. Here, we measure the total testing time according to the number of compute instances. The dataset includes 37,370,466 entries for a 50GB dataset. As the number of computing instances increases, we observe a linear decrease in the total processing time and the total test time with six nodes is approximately 27.6% of the test time with a single-compute node instance. We compare the application hosted by Athena with an application on Spark, and results show Athena introduces a small overhead (under 10%) over the Spark application.

C. Overhead of Athena’s Feature Extraction

We measure the overhead of Athena’s feature extraction while handling external events and compare this overhead to the ONOS baseline (e.g., Cbench benchmark, and CPU usage). We set up an experimental environment with the hexa-core Xeon server to test Cbench benchmark and two hexa-core Xeon servers with seven physical switches to measure CPU usage while gathering events from the switches.

| TABLE IX. Cbench benchmark flow install throughput with and without Athena (response/s) over 50 rounds of testing. |
| --- | --- | --- |
| | MIN | MAX | AVG |
| Without | 773,618 883,376 | 831,366 |
| With | 107,245 610,724 | 389,584 |
| With (no DB) | 631,647 686,227 | 658,514 |
| Overhead (no DB) | 86.13% 30.86% | 53.13% |
| | (18.35%) | (22.31%) | (20.79%) |

1) Cbench benchmark with/without Athena: The ONOS testing group evaluates the scalability of ONOS to measure how many burst events could be handled. For example, they evaluate burst Packet_IN event handling throughput with a single instance, which is called the Cbench benchmark. To do this, we evaluate Athena using Cbench’s throughput mode with the ONOS’s recommended settings [38] and summarize results in Table IX. On average Athena has 53.13% lower throughput and in the worst-case has 86.13% performance degradation. However, without DB operations, Athena induces only 20% performance degradation.

2) CPU usage with/without Athena: The overhead of Athena is dependent on how much information is in the SDN stack, including the control and data plane, as it passively monitors and analyzes them both. To compute the monitoring overhead of handling network events from SDN stacks, we conducted experiments to measure the CPU load when using ONOS with and without Athena. To do this, we established a testing environment with a controller on the hexa-core Xeon server, which is connected to the six physical switches, and 12 OVS instances on the two hexa-core Xeon and the two i5 servers respectively with dummy flows to generate monitoring events. Figure 11 illustrates the testing results. Since Athena stores events to the data plane while maintaining internal status to generate stateful features, the flow handling overhead increases according to the total number of flow entries in the switches. We find that ONOS with Athena saturates at about 140K flows per second, while the CPU utilization is about 31% for the basic ONOS instance.

3) Discussion: We found that the performance overhead of our system primarily originates from MongoDB related operations. To boost Athena’s performance, we will consider replacing MongoDB with a high-performance database like Cassandra [43].

VIII. RELATED WORK

We now discuss how prior projects have sought to address the challenges described in Section II, including various limitations in their coverage. Table X provides a comparison between Athena and existing work related to network anomaly detection and monitoring in SDN environments.

Anomaly detection strategies: The inherent centralized control-layer design of SDNs enables operators an efficient potential network-wide choke-point from which to gather a wide range of network features. In fact, several prior anomaly detection projects [26], [6], [9], [5], [39] have successfully leveraged volume-based network features available through monitoring the OpenFlow protocol to detect network anomalies, such as DDoS attacks and switch anomalies. Mehdi et.al. [8] explored the feasibility of adopting traditional anomaly detection techniques with OpenFlow’s monitoring capabilities, and Braga...
et.al. [10] leveraged OpenFlow statistics to demonstrate low-cost detection of DDoS flooding attacks. FRESCO [37] exports a script-based development environment that facilitates the creation of security applications that monitor well-known network features (e.g., TCP session). However, these efforts do not consider how to fully utilize network features derived from an SDN environment to monitor it for behavioral and operational stability.

From the perspective of detection strategies, most related efforts [26], [6], [9], [5], [39], [8], [10] focus on fixed detection algorithms against specific attacks, not general purpose algorithms. While FRESCO [37] and ATLANTIC [39] provide a set of libraries that aim to facilitate attack detection (e.g., port scanning), only the former provides well-structured mitigation actions and it does not support multi-instance controller environments.

**Scalable SDN monitoring:** Several prior projects have explored various ways to reduce the overhead of gathering volume-based network features [20], [19], [7], [3], [2], [4], [18]. In fact, there have been prior efforts to incorporate a distributed architecture that allows operators to scalably gather network features, such as [17], [2], [18]. However, those projects have not proposed detection strategies for tracking malicious network behaviors. Furthermore, most of these project have assumed the adoption of additional customized switches to perform their scalable network monitoring [17], [18], [4], [3], [2].

Bohatei [16] proposed a scalable DDoS detection and mitigation solution, leveraging an optimization technique that distributes jobs to NFV machines to increase data processing throughput. Bohatei leverages additional NFV devices to perform network functions, and does not directly implement the anomaly detection algorithms. There have also been sampling-based SDN monitoring approaches to reduce collection overhead when collecting statistics from OpenFlow environments [9], [5]. These techniques rely on the adoption of sFlow sampling. Spiffy [26] has demonstrated strategies for Link Flooding Attacks mitigation [25], relying on the SDN’s centralized management to insert flow mitigation. A limitation of Spiffy is that it requires a customized switch to measure the network behavior. Finally, there are several additional projects that have explored the feasibility of anomaly detection in SDNs: [37], [10], [8], [6], [39]. Unlike Athena, none of these projects address our scalability requirements.

**Improving SDN usability:** Several prior projects have introduced northbound APIs that allow operators to conduct various forms of network monitoring [42], [41], [2], [3], [4]. Palmless [40] provides a semantical monitoring capability that helps operators monitor networks by calling well-structured RESTful APIs that reflect a high-level set of monitoring requirements. DNA [17] introduces a scalable network monitoring function to examine telemetry data sources. Although these previous projects enhance usability by exporting well-structured APIs to operators, they do not provide a detection algorithm to find network anomalies.

**IX. Conclusion**

We explore several challenges in designing scalable anomaly detection services in large-scale SDN environments. We evaluate an initial prototype implementation of our solution, Athena, over the open-source ONOS distributed SDN controller. We discuss how Athena enables security researchers and developers to make anomaly detection applications with a minimum of programming effort through its API abstraction layer. We also discuss generalized use of off-the-shelf strategies for driving network anomaly detection algorithm development and introduce a new SDN-specific anomaly.

Athena employs a distributed database and a clustered computing platform, which can deploy these detection algorithms across a large-scale distributed control plane. The Athena framework is designed to operate on existing SDN infrastructures, enabling operators to deploy it in a cost efficient
manner. Our evaluations demonstrate that *Athena* can support well-known network anomaly detection services in an efficient manner, by scaling to a large-scale dataset from a large-scale datacenter-like physical network environment. *Athena* has been publicly released as an open-source project to the academic and SDN research community.

ACKNOWLEDGMENT

This work was supported by the ICT R&D program of MSIP/IITP, Republic of Korea [No. B0190-16-2011, Korea-US Collaborative Research on SDN/NFV Security/Network Management and Testbed Build]. This material is based upon work supported by the National Science Foundation under Grant Numbers 1446426 and 1642150. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

REFERENCES


