Unsupervised Anomaly Alerting for IoT-Gateway Monitoring using Adaptive Thresholds and Half-Space Trees

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***Abstract*—Through increasingly powerful hardware, the computational resources of IoT-Gateways are growing, enabling more sophisticated data analytics, service deployments and virtualisation capabilities. However, the difficulty of ensuring high reliability of IoT-Gateways and its deployed services increases along with the complexity of digital systems. Reliable operation of such gateways and devices therefore depends on automated methods for detecting abnormal behaviour as early as possible, in order to remediate the situation before the complete failure of a system component.**

We propose an unsupervised anomaly detection algorithm by extending the concept of Half-Space Trees through online adaptive thresholds for real-time computation. The anomaly detector consumes multidimensional time series data from an external monitoring component and is fixed in computational complexity to support real-time operation. In order to determine valuable hyperparameters, we propose a data stream and anomaly simulation system, providing options for pattern induced load simulations and different types of anomalies. Further, we evaluate the anomaly detection method on monitoring data originating from a deployment of the open source software Project Clearwater, a lightweight implementation of the IP-Multimedia Subsystem capable of running on VMs with limited resources. Results show the applicability of Half-Space Tree based anomaly detection with high detection rates (99.4%) and low number of false alarms (< 3%).

***Index Terms*—anomaly detection; reliability; gateways**

I. Introduction

The rapid progress of digitalisation in the public and private sector opens opportunities for the development of new smart and connected devices in a wide range of fields, including medical self-tracking, smart factories, home gardening, and many others. Main drivers of this development are the emerging connectivity driven by the 5G movement and increasing affordability and availability of compute resources. Highly compact barebone computers or smartphones are now capable of running multiple apps and services and even provide virtualisation environments (e.g. Raspberry Pi running Kubernetes). There are many potential applications for using such devices as IoT-Gateways for forwarding sensor data or requesting computation-intensive services. However, powerful computation and virtualisation capabilities engender new problems that arise from the deep technological stack and complex overall system architecture. These problems are exacerbated in the IoT domain, where high reliability is a prerequisite and often seen as a commodity.

Reliable operation of distributed small-sized devices and services consists of a variety of tasks, including identification of problematic behaviour and security threats, finding the root cause in an anomaly situation, and the selection and execution of an appropriate counter measure. At the scale of todays IoT systems, these tasks are impossible to perform manually for human system administrators [1]. Therefore, automatic anomaly detection algorithms play an important role in the reliable operation of IoT infrastructures.

The domain of IoT-Gateways introduces special requirements and challenges when designing anomaly detection methods. Firstly, in contrast to data centers and computation in the cloud, an IoT-Gateway has very limited resources. An anomaly detection algorithm on such a device must be able to analyse a data stream in a timely manner, while consuming a minimal amount of computational resources and memory. Furthermore, the resources of an IoT-Gateway device are shared between productive code and the data analysis processes. Since the productive parts of the system are prioritised, the resources available to anomaly detection are reduced even further.

The IoT landscape exhibits many types of anomalies, including intrusion attempts, DDoS attacks, software bugs, hardware failures, etc. We define anomalies as degraded states of the system impacting the service quality, which the device shall deliver. Thus, we aim to detect anomalies before the services or devices fail, in order to allow countermeasures to resolve the underlying problem. In this work, we further limit the scope to resource anomalies like memory leaks, insufficient network bandwidth, or excessive CPU utilisation.

The state of the art approach for detecting anomalous behaviour is based on expert-defined thresholds that trigger alerts, which are then evaluated by system administrators. The thresholds are applied to data from active or passive monitoring tools, which are commonly used in computing infrastructures. This approach has limited applicability to IoT-

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Gateways, where resource usage patterns vary and system load changes frequently. Manual thresholds are difficult to maintain and must be constantly adapted in order to guarantee a high detection rate and a low number of false alarms. This leads to stale alarm threshold definitions and a low quality of anomaly detection results.

In order to address these shortcomings, this paper introduces the three following key contributions:

1) We propose a novel, unsupervised anomaly detection approach for automated alerting of abnormal system behaviour. The goal of our approach is to detect abnormal behaviour before a component fails entirely. The approach is based on the machine learning algorithm Half-Space Trees (HS-Trees) [2] and is extended by combining HS-Trees with dynamic threshold functions [3], [4] to adapt to concept drifts and enable online detection capabilities without a separate training phase with labelled data.
2) Further, we present an anomaly simulation environment for evaluating suitable hyperparameters of the proposed algorithm. The simulator produces a data stream by generating a varying time series signal and injecting simulated anomalies at variable frequencies, comparable to the capabilities of the seasonal time series generator module in WEKA [5].
3) Lastly, we provide an evaluation on a testbed for simulating resource limited IoT-Gateways. The resource usage of the simulated devices is monitored and analysed by the proposed anomaly detection algorithm. Anomalies are injected through a specialised anomaly injection framework, capable of creating real memory leaks, resource fluctuations and other high load scenarios. The testbed runs an installation of Project Clearwater, an open source implementation of the IP Multimedia Subsystem, on several compact virtual machines, which represent many IoT-Gateways.

The remainder of the paper is structured as follows; Section II presents related approaches capturing the state of the art of further anomaly and state change detection methods. In Section III, we provide background about the HS-trees anomaly detection approach. Afterwards, we describe the extended Half-Space Trees anomaly detection approach in Section IV, while Section V shows an extensive anomaly simulation framework for hyperparameter optimisation. Section VI evaluates the unsupervised anomaly detection approach using data from the Clearwater service testbed. Finally, Section VII concludes this paper and gives an outlook for future work.

II. Related Work

Anomaly detection is a long standing and widely researched area with applications in diverse domains. The proposed approaches can be grouped into the two different categories: Supervised and unsupervised methods.

Supervised approaches use labelled system information to train the machine learning models. Put briefly, the anomaly detection algorithms employ either classification or regression models trained using data containing the information whether the data point is anomalous or not.

Sauvanaud et al. [6] examine a supervised ensemble approach for anomaly detection in their work. They combine several different supervised classification algorithms, performing anomaly detection for individual services by using a weighted voting mechanism. Thus, the collection of algorithms predicts whether a component is normal or not. The evaluation is based on a Virtual Network Function scenario similar to our setup as presented in this work. Also, Liu et al. [7] propose a supervised anomaly detection strategy. They base it on the concept of self organising maps (SOM). The SOMs are configured to represent the whole infrastructure in order to predict the overall performance of the system. Based on this model, they show that anomalies within virtual machines can be detected in related regions of the infrastructure. In contrast to this work, we are not limited aggregate data from several hosts, but can also create models per individual host in order to capture its own behaviour for decentralised computation purposes.

Supervised approaches' characteristic of consuming labelled training data can pose challenges. Providing sufficient labelled training data by expert-labelling may not be feasible as manual labelling is too time consuming. Automatic creation of training data sets typically relies on the assumption that one can collect such data from a running system. Doing so could potentially harm the productive system and is therefore undesirable. For practical use, unsupervised methods are therefore investigated, bearing the positive properties of performing the same task without using labelled input data. Thus, our work aims to provide an unsupervised detection technique.

Dean et al. [8] also utilise SOMs, but propose an unsupervised detection model. They aim to predict failures within a cloud infrastructure, but do not consider degraded state anomalies as a use case. In contrast to these deep learning models, Cotroneo et al. [9] use simple statistical correlation analysis between system components in order to automatically detect anomalies. Changes within these correlations are predicted as anomalies. Again, the focus of Cotroneo et al. [9] is to combine data from different hosts. This approach suffers from scalability issues when applied to dynamic service and infrastructure environments. Thus, we aim to create unsupervised detection models for individual hosts, which can be applied directly on the monitored entity.

Malhotra et al. [10] describe a method of training a neural network with LSTM cells on time series data in order to learn its representation. Through a dedicated training phase a Gaussian distribution is learned on the representation errors. Thus, user defined thresholds can be used to decide which data is close enough to be expected as normal or otherwise reported as anomaly. Hundman et al. [4] use a similar LSTM-based network approach but include dynamic thresholds based on exponential moving averaging reconstruction errors. This provides the possibility to adapt to concept drifts over time. Both works [4], [10] influenced our proposed technique as we also aim to evaluate dynamic thresholds as well as anomaly scoring, which is similar to the reconstruction error based

approach. Chandola et al. [11] aggregate further concepts for anomaly detection techniques used in this field in a survey.

III. Half-Space Trees Background

Streaming Half-Space Trees (we will refer to it by *HST*) is an online anomaly detection algorithm proposed by Tan et al. [2], capable of unsupervised learning on multidimensional data-streams with continuous numerical attributes. It requires the data-stream to have constant dimensionality, as well as prior knowledge of the number of dimensions and each dimension's upper and lower bounds. We will consider data points within a stream as arrays of fixed size and refer to the space spanned by the stream's known bounds as the domain.

The basic idea of the algorithm is to split the domain into a series of nested sub-spaces, or regions, utilising a complete binary tree structure, called Half-Space Trees [2]. Each node of one of these binary trees has a part of the original domain associated to it, which we will call the node's work space. If a node has children, its work space is split into disjunct, equal-volume halves along a hyperplane bisecting a dimension chosen at random and each half is assigned to one of them. The work space of the root contains the entire domain. Thus, any data point in the domain can traverse a unique path from the root of a HST to one of its leaves along the nodes whose work spaces it is contained in.

The data-stream is then also partitioned into short *windows* of a set length of $w \in \mathbb{N}$ data points. At any given time, we only consider two consecutive windows, the current one, called latest window, and the preceding one, referred to as the reference window. Once w data points have been recorded in a latest window, it is considered full, and becomes the reference window. With the next arriving data point, a new latest window begins. A data stream's structure is recorded as a *mass profile* [12], where each node has two counters r and l: r for the *reference mass profile* and l for the *latest mass profile*. A node's latest mass profile counter l is incremented by one when a newly arrived data point traverses it on its path to a leaf. Once the latest window is full, the reference mass profile counters of every node are overwritten with the value of their respective latest mass profile counters, which are then reset to 0. See figure 1 for a visual representation of a Streaming HST and a recorded latest mass profile.

To aid the algorithm's robustness, an ensemble of $n \in \mathbb{N}_{>0}$ Half-Space Trees is created. To facilitate further diversity, the work spaces assigned to each tree's root are not the domain but a random perturbation of it which must contain it.

Anomaly prediction is performed by assigning an *anomaly score* to each data point upon its arrival. A score is calculated independently for each tree in the ensemble, the final anomaly score is the sum of all of these scores. We will refer to the score calculated for a data point x on a single tree T by $S(x,T)$, while denoting the final anomaly score over all trees with $S(x)$. $S(x,T)$ is calculated by letting the data point x traverse the tree T until a node is reached that is either a leaf, or has a reference mass profile equal to or less than a user-determined variable s as size limit. Tan et al. suggest a value of $0.1 \cdot w$, which we will also use for our evaluations. We will refer to that final Node by $Node^*$, we refer to the depth of a node in the tree by $Node.depth$ (note: roots have depth 0) and to its reference mass by $Node.r$, and can now calculate

$$S(x,T) := Node^*.r \cdot 2^{Node^*.depth}.$$

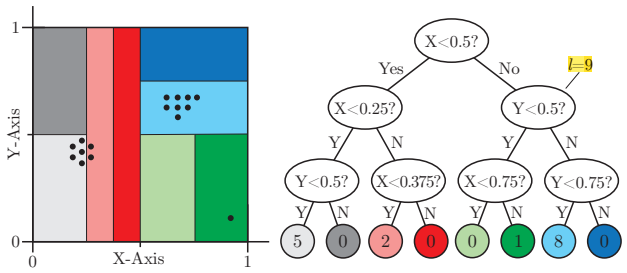

Fig. 1. Right: An HS-Tree of height 3. Inner nodes contain their splitting dimension and value, leaves contain counters for the latest window mass profile. The root's right child also has the value of its latest mass profile counter marked. Left: Both dimensions of the two-dimensional domain are bounded by $[0,1]$ and the domain is partitioned by the HS-Tree. Points represent data points. (Figure based on figure 1 in [2])

Due to the limit of s and the different weights applied to a score according to the depth to which a new data point traversed, smaller variations in a data stream's distribution will not lead to an immediate drop of new data point's anomaly scores to 0. While this allows the algorithm to be applied to data streams with concept drift, it also means that anomalous data points may not result in anomaly scores of 0.

The algorithm itself needs few parameters. The authors describe its performance on a given data stream as somewhat independent of the algorithm's parametrisation.

Tan et al. [2] propose recording all data points along with their corresponding anomaly scores and sorting them by their anomaly scores in descending order. The anomalous data points may then be found at the bottom of the list. Accordingly, a prediction for any given data point can only be made once the data stream has ended, as it is only then that the data can be ranked using this approach. Additionally, the percentage of anomalies in the stream must be known in advance in order to determine the number of data points at the bottom to predict as anomalous.

This approach also relies on the assumption that anomalies are rare and fleeting, as continued and homogeneous anomalies will eventually be recorded in the reference mass profile and be predicted as normal. We will share this assumption for our approach.

IV. Unsupervised Anomaly Detection using Adaptive Thresholds

We propose a method that allows us to predict whether any given data point in the stream is anomalous immediately after its anomaly score has been calculated. We achieve this by introducing adaptive thresholds generated on the basis of the anomaly scores calculated for preceding points in the data stream.

We assume that thresholds viable for diverse data sets must be adaptive to allow for changes in the distribution of the anomaly scores when concept drift in the data stream sets in or ceases. We also assume that the anomaly scores HST generates for any given data stream are normally distributed, similar to reconstruction-based scoring models used in [4], [10], [13]. Thus, the main idea relies on constructing a dynamic, point-wise threshold based on the anomaly scores of points assumed to be normal.

Based on these assumptions, we have extended HST by introducing a threshold that is updated iteratively with each new anomaly score, generated using Tony Finch's Exponentially Weighted Moving Standard Deviation (EWSD) [14]. We compare a new anomaly score with the latest threshold. If the new anomaly score is lower than that threshold, we predict the data point associated with the anomaly score as anomalous. This allows us to make a prediction for a newly arrived data point immediately after its arrival. We then update the threshold using that latest anomaly score t.

The EWSD is calculated on the basis of the Exponentially Weighted Moving Average (EMA) proposed by J. Stuart Hunter [15]. The EMA generates a weighted average by applying weights which decrease exponentially for older values and allows continuous introduction of new values without impact on performance. The EWSD is a weighted standard deviation, weighted using the same mechanism as EMA, that's efficiently updated along with the EMA. To facilitate the calculation of the EWSD, we will also introduce the Exponentially Weighted Moving Variance, which we will call *EMVar*.

The user can choose a variable $\alpha \in (0,1)$ that determines the weighting. We will refer to the current EMA after the i-th data point of the stream x_i has been inserted as EMA_i, the corresponding EMVar as $EMVar_i$ and the EWSD as $\widetilde{\sigma}_i$. Let $EMA_1 := S(x_1)$, $EMVar_1 := 0$ and $\widetilde{\sigma}_1 := 0$. Every further value is calculated by

$$\begin{aligned} \delta_i &:= S(x_i) - EMA_{i-1}\,, \\ EMA_i &:= EMA_{i-1} + \alpha \cdot \delta_i \\ &= \alpha \cdot S(x_i) + (1-\alpha) \cdot EMA_{i-1}\,, \\ EMVar_i &:= (1-\alpha) \cdot (EMVar_{i-1} + \alpha \cdot \delta_i^2)\,, \\ \widetilde{\sigma}_i &:= \sqrt{EMVar_i}\,. \end{aligned}$$

The current threshold t is then calculated using a user-determined constant $\eta \in \mathbb{R}_+$, and constantly overwritten after each new anomaly score has been inserted, according to the following formula:

$$t := EMA_i - \eta \cdot \widetilde{\sigma}_i \ .$$

We have decided against only using anomaly scores predicted as normal to update EMA and EWSD, to allow for fast recovery in cases where our threshold might mistakenly interpret concept drift as anomalies.

V. Parameter Optimisation

In order to evaluate suitable hyperparameters for our anomaly detection approach, we propose a method for data stream simulation that enables researchers to test their anomaly detection algorithms on a locally generated artificial data stream. Our method allows for a wide variety of settings that let users evaluate their approaches' robustness by testing them against simulated data streams of varied complexity.

Our data stream simulator allows us to produce a multidimensional data stream with concept drift. In our implementation, we concentrated on certain aspects of our proposal that were best suited for a data stream based on assumptions about the expected properties of IoT-Gateway load usage, in order to find parameters for our adaptive thresholds that would yield a robust anomaly detection algorithm capable of working on a wide range of data streams.

A. Anomaly Event Simulator

We propose a data stream simulator that incorporates both regular system patterns and anomalies. It outputs one data point at a time upon request. The features of each dimension of the data stream drift at a constant rate, which may differ between dimensions. We assume that anomaly detection algorithms that, like HST, require the domain of the data stream to be bounded in every dimension are independent of the actual bounds, since we can normalise each dimension's domain to the same interval $[x,y]$ with $x,y \in \mathbb{R}$ using a bijective mapping. Due to this and the mechanisms by which HST splits the domain into regions and records a data stream's structure, our simulated data stream's domain can have homogeneous upper and lower bounds across all dimensions without compromising our results' applicability to real-world data. Table I shows and describes the different parameters for the anomaly data stream generator.

Normal system behaviour is generated mainly based on the choices concerning *sinus*, *minStepSize* and *maxStepSize* which determine the shape and rate of fluctuation. For example, the angular trajectory pattern describes normal points as: The initial data point is defined on all dimensions as $min + |max - min| \cdot minNormal$. Succeeding data points change at an interval chosen randomly by uniform distribution between *minStepSize* and *maxStepSize* inclusively until reaching or exceeding $min + |max - min| \cdot maxNormal$. The direction is then reverted, such that it aims again to the initial starting point. This behaviour is shown in Figure 2.

Once *cleanPoints* have been generated, a random number generator is used to inject anomalies into the dimensions with index *firstAnomalyDim* to that index plus *anomalyDims*. According to the probability set in *anomalyPercentage*, the anomaly generator decides point-wise whether an anomaly will be injected into the data stream. Am anomaly is created by setting the new data point's value on the anomaly dimensions to *min* or *max*, depending on which has greater distance to the last generated value on that dimension. The value *anomalyLength* describes for how many data points the anomaly continues. Figure 3 shows such a point anomaly on a dimension with an angular trajectory pattern.

TABLE I
PARAMETERS DETERMINING THE STRUCTURE OF A SIMULATED DATA STREAM.

nrOfDims	Number of dimensions in the data stream.
min & *max*	Upper and lower bound for all dimensions.
minNormal & *maxNormal*	Relative upper and lower bound of the "tunnel" within a dimension in which normal data points fluctuate.
minStepSize & *maxStepSize*	Minimal and maximal rate of fluctuation in a dimension per data point, ex. 0.1 for $0.1 \cdot \lvert max - min \rvert$.
anomalyPercentage	Anomaly rate in the data stream.
anomalyLength	Length of an anomaly (number of data points it lasts for).
firstAnomalyDim	First dimension of the data stream to be affected by anomalies.
anomalyDims	Number of dimensions affected by an anomaly. Anomaly dimensions occur in a block starting with *firstAnomalyDim*.
randomise	Boolean that determines whether fluctuation rate will be chosen at random from $[minStepSize, maxStepSize]$, or decrease linearly between dimensions 1 and *nrOfDims* from *maxStepSize* to *minStepSize*.
cleanPoints	Number of clean data points at the beginning of the stream. May be needed for unsupervised anomaly detection algorithms.
sinus	Boolean that determines whether values of each dimension follow a sinus curve or an angular trajectory.

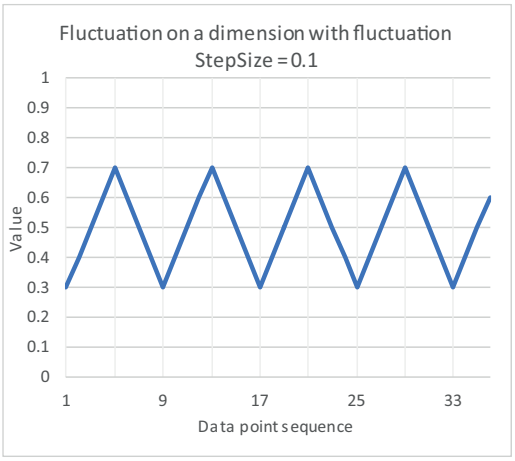

Fig. 2. Example for fluctuation on a single dimension of a data stream with $StepSize = 0.1$, $min = 0$, $max = 1$, $minNormal = 0.3$, $maxNormal = 0.7$.

B. Parameter Evaluation

For hyperparmeter evaluation, we generated a data stream using the setup parameters shown in Table II. Furthermore, we focused on the hyperparameters for our adaptive threshold EWSD in order to identify an advantageous hyperparameter setup for our dynamic threshold extension. For HST, we also use the hyperparameters Tan et al. [2] provided in their paper's base setups. Therefore, the window size is set to $w = 250$, size limit to $l = 0.1 \cdot w$, number of trees $n = 25$ and the maximum depth of a tree is set to $d = 15$.

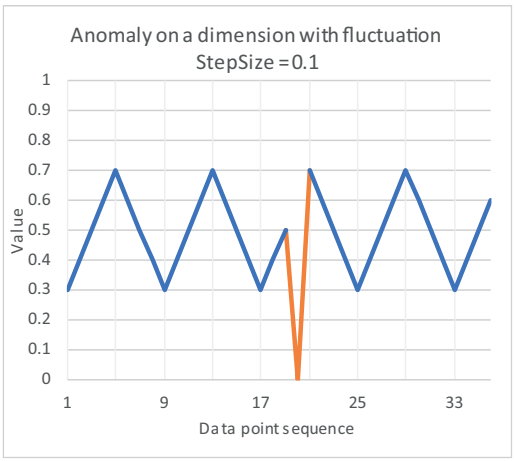

Fig. 3. Example of an anomaly with $anomalyLength = 1$ on the dimension from figure 2.

C. Setup for HST+EWSD Parameter Search

TABLE II
DATA STREAM SIMULATOR PARAMETERS WE HAVE USED FOR HST+EWSD HYPERPARAMETER OPTIMISATION.

nrOfDims	30
min & *max*	0 & 1
minNormal & *maxNormal*	0.3 & 0.7
minStepSize & *maxStepSize*	0.001 & 0.1
anomalyPercentage	2 %
anomalyLength	1
firstAnomalyDim	15
anomalyDims	2
randomise	FALSE
cleanPoints	*w*
sinus	FALSE

Given this setup, the scatter plot in Figure 4 illustrates the anomaly scores generated by HST over time during a single window. Blue dots represent normal behaviour, while larger orange dots represent anomalies. As expected, lower scores indicate higher rates of change, which in turn indicate abnormal data points. However, a clear border seems not to be easily defined, which can also be seen in Figure 5, showing the histogram of the same sample window's scores.

For our threshold evaluation we executed a grid search of hyperparameters α and η where we extensively evaluated large setups. For this paper, we will concentrate on key frames from the larger grid search indicating highest value of information for identifying suitable parameters. The next section shows our results of the grid search in the intervals $\alpha = [0.06, 0.18]$ with step size 0.04 and $\eta = [0.6, 1.8]$ with step size 0.4.

D. Parameter Results

For evaluation purposes, we selected the true positive rate (percentage of anomalies which were correctly detected as anomalies) and true negative rate (percentage of normal data

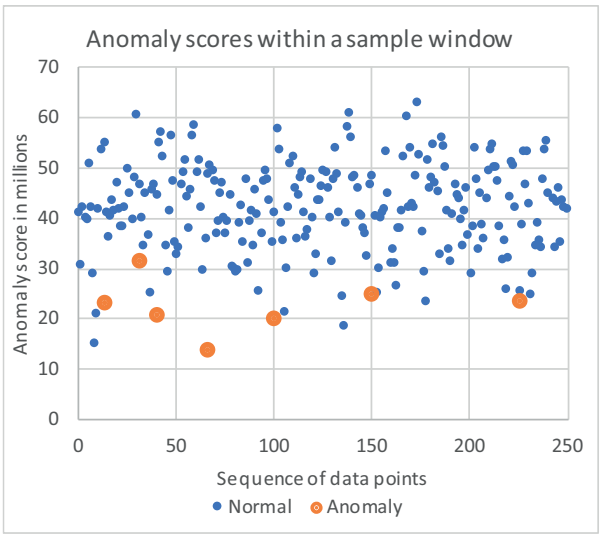

Fig. 4. A visualisation of anomaly scores within a sample window. Smaller blue dots represent anomaly scores of normal data points, larger orange dots represent those of anomalies we have injected.

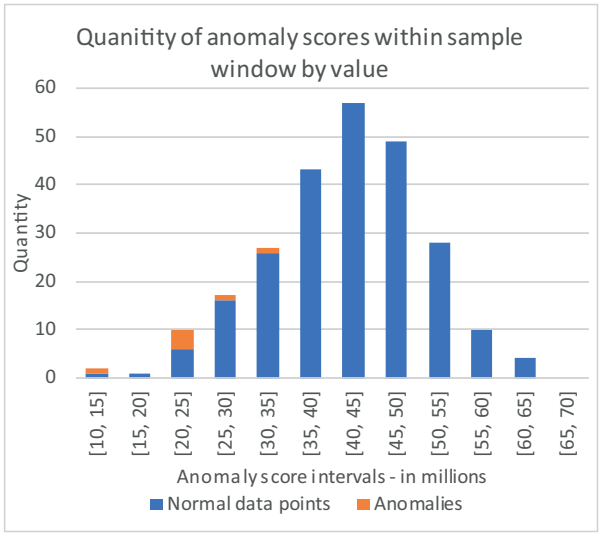

Fig. 5. Empirical distribution of data points in figure 4.

points which were correctly classified as normal). Figure 6 shows the results for both parameters. The image indicates that increasing the value of η decreases the anomaly detection rate while increasing correct classification of normal points. It also indicates that very high or low values for α are detrimental to the true positive rate.

We have chosen ($\eta = 1.4$, $\alpha = 0.14$) for further evaluation, since we found a higher true negative rate to be more desirable for our purposes. In the next section, we will evaluate our approach using these hyperparameters on a service testbed, running lightweight software on a compact virtual machine, representing a small IoT-Gateway.

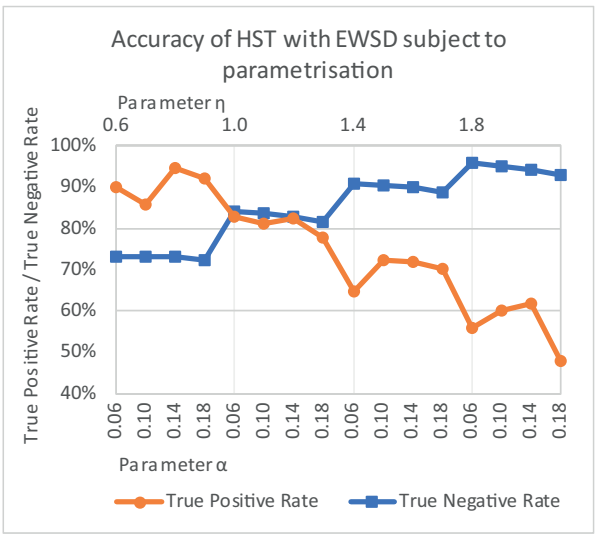

Fig. 6. Accuracy of the HST+EWSD algorithm subject to differing parametrisation of the adaptive thresholding algorithm.

VI. IoT-Gateway Evaluation

For evaluating the applicability of our solution to IoT-Gateway devices, we present a testbed simulating typical service components running on a gateway device utilising available open source solutions. Next, the service components are described in detail, followed by a description of the infrastructure.

A. Service Setup

We deployed an open source implementation of an IP multimedia subsystem (IMS), Project Clearwater[1]. Clearwater is considered as one of the first examples for virtual network functions, which makes it highly interesting to telco-providers, regarding services in the access network or even on gateway devices. IMS is an emerging architecture for IP-based telecommunication services, such as voice- or video calls or messaging. The core implementation of Clearwater allows users to register, and handles the initiation process to connect calls. This initiation process mainly consists of retrieving information about the user authentication and querying users' connection details needed to initiate the call. The call itself is not handled by Clearwater. We will consider the Clearwater services Bono, Sprout, Homestead and Ellis within the experiment.

Bono functions as edge proxy, handling client connections. Clients can register via the SIP protocol in order to initiate calls. The requests are then routed to the Sprout service.

Sprout manages the different communications to other internal services, e.g. authentication requests.

Homestead contains the client profile information needed to authenticate clients.

Ellis obtains the information for the management unit, as such it functions as an account management system.

[1]http://www.projectclearwater.org/

In order to provide realistic results, we simulate usage of the IMS by changing the number of client registrations and call initiations randomly between 20 and 40 users every minute. Furthermore, we deployed a replicated version which is load balanced. Thus, the key services Bono and Sprout are deployed three times each, while single deployments are used for Homestead and Ellis.

B. Infrastructure Setup

We use a balanced and replicated Openstack[2] installation as cloud infrastructure. Through Openstack, it is possible to create virtual machines, in which we deploy the services described above. For each service installation, we created its own virtual machine. The virtual machines run Ubuntu 14.04 and use 2 vCPU cores, 2GB memory and 20GB disk.

For monitoring, we collect resource usage data parsing the proc filesystem, provided by the operating system, inside each virtual machine. The data collection interval is 500ms.

C. Anomaly Injection

In order to evaluate the proposed approach, we simulate a larger set of resource anomalous behaviours in the system. To that end, we developed an injection agent handling several different anomalies. The agent is placed inside each virtual machine and can execute the following anomalies:

- *Disk* pollution, temporary disk pollution and HDD stress: Both anomalies are writing data into a log-file. For the temporary case, the files are deleted, otherwise the file is retained. HDD stress describes an excessive hard disk usage by writing a file.
- *CPU* stress, leak and fluctuation: CPU stress immediately consumes excessive amounts of CPU. CPU leakage describes an anomaly increasing in its intensity over time by consuming more and more CPU. CPU fluctuation constantly increases and decreases the CPU usage in order to provide a fluctuation behaviour.
- *Memory* stress, leak and fluctuation: Memory anomalies are modelled similar to CPU anomalies: immediately consuming high amounts of memory, growing consumption over time and fluctuating allocation of memory.
- *Fork* flooding leak and fluctuation: A process starts to create child processes over time. For the leakage variant, those child processes create more processes, while in the fluctuation variant children are partly removed.
- *Large file* download: A process starts downloading a large file, resulting in high network traffic.
- *File pointer* wasting: Creates a leakage of file pointer IDs over time by requesting but not releasing them.

Normal behaviour (NR): Between the introduction of different anomalies, we always observe phases where the whole system runs without anomalies, which we consider as normal behaviour.

Through using several simulated anomalies with different behaviours, we intend to show the robustness of our anomaly detection approach. Notably, the intensity increase of each anomaly can be configured and is randomly selected for the current evaluation.

[2]https://www.openstack.org/

D. Analysis Pipeline Configuration

As described above, we collect metrics from the proc filesystem, consisting of 29 values. Before performing anomaly detection on the data, we do a preprocessing step, min-max scaling each metric in order to normalise the data in a fixed range $[0,1]$. The scaling of an individual metric is performed by calculating $\hat{x} = \frac{x - x_{min}}{x_{max} - x_{min}}$ for the value x of a metric of an incoming data point, where x_{min} and x_{max} represent the minimum and maximum values for that metric. The bounds can be inferred over time or set by an expert.

Using this evaluation setup, we collected data of all services for 72h. The first 20 minutes of data consists of normal data grace time. Afterwards, the anomalies were injected in a round-robin manner to the individual service hosts for 3 minutes. Between the execution of anomalies, a cool down of 1 minute is performed. For evaluation purposes, we used data sets for each individual host, containing anomalies running on that specific host and time frames where the system runs in normal mode.

E. Evaluation Results

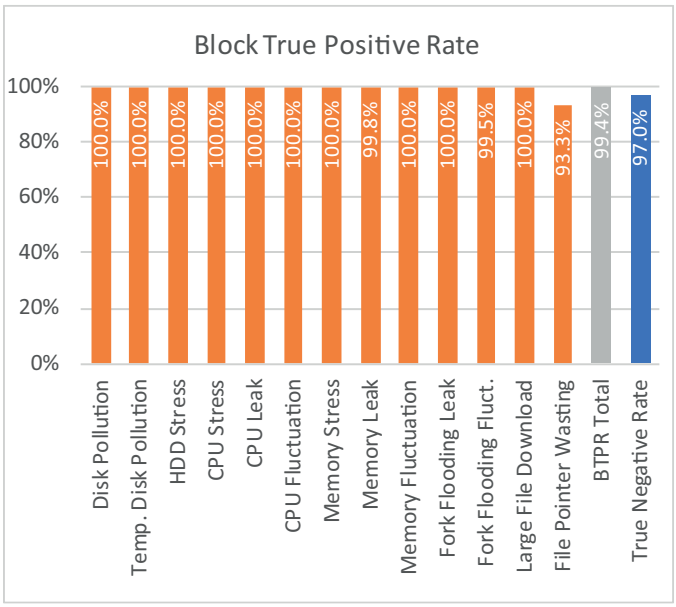

Fig. 7. Detection accuracy of the HST+EWSD algorithm on an the IoT-Gateway data stream.

For more meaningful evaluation results, we decided to measure the percentage of detected anomaly events, not individual data points. An anomaly event is a block of a single type of anomaly, which appears for a certain amount of time. In our setup, such blocks have a size of 3min, thus contain 360 data points due to the monitoring interval. For each anomaly type we have 56-59 blocks of anomalies in total. Furthermore, we

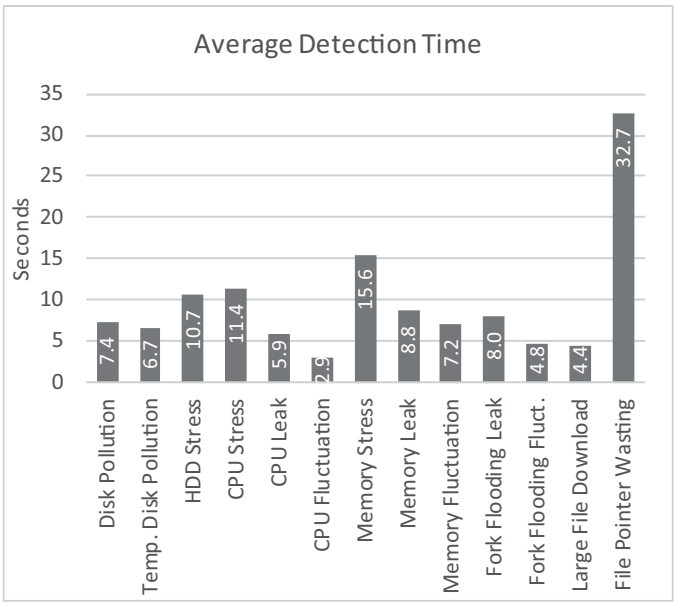

Fig. 8. Average anomaly detection time of the HST+EWSD algorithm on an IoT-Gateway data stream.

consider the detection time, the difference between the initiation of the anomaly injection and its detection. Additionally, we consider the point-wise true negative rate, which indicates how accurately the normal data points where detected, which also allows us to induce the false alarm rate.

Figure 7 shows the detection results and the true negative rate. The detection results (orange) show, that almost all abnormal events were detected ($> 99\%$), except file pointer wasting (93.3%). Through detailed investigation, it seems to be difficult for even administration experts to see this abnormal behaviour within the data. We therefore assume that for this type of anomaly, more precise metrics need to be included or further feature engineering is needed to provide data which can be used to detect such anomalies. Overall, the detection rate of all anomaly events (BTPR Total, grey), the results show a strong accuracy of 99.4%.

Figure 8 gives insights about average anomaly detection time. As with the anomaly detection rate, file pointer wasting shows least accurate performance, with 32.7sec detection time (not including runs where it was not detected at all). Other anomalies were detected in much faster 7.8sec on average.

The true negative rate (Fig. 7, blue) also shows very good results with 97%, but still provides room for improvements, as 3% of data points were false positives. Telco-providers, for instance, require a reliability of 99.999% [16] in order to provide production ready solutions to meet their aimed SLAs.

VII. Conclusion

This work presented an unsupervised anomaly event detection approach, which extended the Half-Space Trees algorithm by Tan et al. [2] using dynamic threshold definition, enabling point-wise detection. We showed how valuable hyperparameters can be found by introducing an anomaly data stream simulation framework. Furthermore, the anomaly detection algorithm was evaluated using a testbed simulating IoT-Gateway devices through compact virtual machines running an IMS service use case. Through injecting different types of resource anomalies, we showed that the approach achieves high detection rates ($> 99\%$) for all anomalies with a small number of false alarms ($< 3\%$).

In future, we would like to evaluate this approach on further services use cases and extend the evaluation on virtual machines of different sizes in order to provide more insights about computation bottlenecks with respect to resource usages. Furthermore, we would like to investigate different device usage patterns in more detail to simulate more accurate system load. Furthermore, we envision to provide an extensive study of different anomaly detection algorithms to provide the possibility for future zero touch administration.

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