Distributed Novelty Detection at the Edge for IoT Network Security ⋆

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Abstract. The ongoing implementation of the Internet of Things (IoT) is sharply increasing the number and variety of small devices on edge networks. Likewise, the attack opportunities for hostile agents also increases, requiring more effort from network administrators and strategies to detect and react to those threats. For a network security system to operate in the context of edge and IoT, it has to comply with processing, storage and energy requirements alongside traditional requirements for stream and network analysis like accuracy and scalability. Using a previously defined architecture (IDSA-IoT), we address the construction and evaluation of a support mechanism for distributed Network Intrusion Detection Systems (NIDS) based on the MINAS Data Stream Novelty Detection (DSND) algorithm. We discuss the algorithm steps, how it can be deployed in a distributed environment, the impacts on the accuracy and evaluate performance and scalability using a cluster of constrained devices commonly found in IoT scenarios. The obtained results show a negligible accuracy loss in the distributed version, but also a small reduction in the execution time using low profile devices. Although not efficient, the parallel version showed to be viable as the proposed granularity provides equivalent accuracy and response times.

Keywords: novelty detection · intrusion detection · data streams · distributed system · edge computing · internet of things

1 Introduction

The Internet of Things (IoT) brings together a wide variety of devices, including mobile, wearable, consumer electronics, automotive, and sensors of various types. Such devices can either be accessed by users through the Internet or connect to other devices, servers, and applications, with little human intervention or supervision [15,1,8,13]. Security and privacy is a major concern in the IoT, specially regarding devices having access to user personal data like location, health, and many other sensitive data [12]. Furthermore, if compromised, such devices

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can also be used to attack other devices and systems, steal information, cause immediate physical damage or perform various other malicious acts [9]. As an additional concern, IoT devices likely have long lifespan, less frequent software patches, growing diversity of technologies combined with lack of control over the software and hardware of such devices by the host organization (where their are deployed), which considerably increases the attack surface.

Because most IoT devices have limited resources (i.e., battery, processing, memory, and bandwidth), configurable and expensive algorithm-based security techniques are not usual, giving way to network based approaches [17]. Machine Learning (ML) techniques, for instance, have been studied for years to detect attacks from known patterns or to discover new attacks at an early stage [2,11]. A recent survey [15] shows that ML based methods are a promising alternative which can provide potential security tools for the IoT network making them more reliable and accessible than before.

Despite the promising use of ML to secure IoT systems, studies found in the literature [2,11,15] are limited to traditional ML methods that use static models of traffic behavior. Most existing ML solutions for network-based intrusion detection cannot maintain their reliability over time when facing evolving attacks [16,10]. Unlike traditional methods, stream mining algorithms can be applied to intrusion detection with several advantages, such as: (*i*) processing traffic data with a single read; (*ii*) working with limited memory (allowing the implementation in small devices commonly employed in edge services); (*iii*) producing real-time response; and (*iv*) detecting novelty and changes in concepts already learned.

Given the recent [16,10,4] use of Data Stream Novelty Detection (DSND) in network data streams, this paper shows the effects of adapting these mechanisms to edge services for use in IoT environments. Our proposal, called *MFOG*, adapted and experimentally validated the IDSA-IoT architecture [3] using the DSND algorithm MINAS [5,7], making the algorithm suitable to run on a distributed system composed of small devices with limited resources on the edge of the network. Using our newer version of the MINAS algorithm, We have experimentally evaluated how the distribution affects the capability to detect changes (novelty) in traffic patterns, and its impact on the computational efficiency. Finally, some distribution strategies and policies for the data stream novelty detection system are discussed.

This paper is organized as follows: Section 2 reviews the chosen DSND algorithm MINAS. A distributed extension of MINAS, including its implementation and evaluation are presented in Section 3 and in Section 4 we show how we evaluated *MFOG* and the discuss results we found. Finally, Section 5 summarizes the main findings and presents possible future work.

2 MINAS

MINAS [5,7] is an offline-online DSND algorithm, meaning it has two distinct phases. The first phase (offline) creates a initial model set with several clusters based on a clustering algorithm with a training set. Each cluster can be associated with only one class of the problem, but each class can have many clusters.

During its online phase, which is the main focus of our work, MINAS performs three tasks in (near) real-time, in summary, classification, novelty detection, and model update tasks in a potentially infinite data stream, as shown in Algorithm 1.

MINAS attempts to to classify each incoming unlabeled instance according to the current decision model. Instances not explained by the current model receive an *unknown* label and are stored in a unknowns-buffer. When the unknowns-buffer reaches a preset threshold, MINAS executes the Novelty Detection function. After a set interval, samples in the unknowns-buffer are considered to be noise or outliers and removed. The algorithm alo has a mechanism to forget clusters that became obsolete and unrepresentative of the current data stream distribution, removing them from the Model and storing in a Sleep Model for possible recurring pattern detection [7].

```
Input: ModelSet, inputStream
Output: outputStream
Parameters: cleaningWindow, noveltyDetectionTrigger
Function MinasOnline(ModelSet, inputStream):
  UnkownSet ← ∅, ModelSleepSet ← ∅ ;
  lastCleanup ← 0 , noveltyIndex ← 0;
  foreach sample_i ∈ inputStream do
    nearest ← nearestCluster (sample, ModelSet);
    if nearest.distance < nearest.cluster.radius then
      sample.label ← nearest.cluster.label;
      nearest.cluster.lastUsed ← i ;
    else
      sample.label ← unknown;
      UnkownSet ← UnkownSet ∪ sample;
      if | UnkownSet | ≥ noveltyDetectionTrigger then
        novelties ← NoveltyDetection (ModelSet ∪ ModelSleepSet,
          *UnkownSet);
        ModelSet ← ModelSet ∪ novelties;
      if i > ( lastCleanup + cleaningWindow) then
        ModelSet ← moveToSleep (ModelSet, *ModelSleepSet, lastCleanup);
        UnkownSet ← removeOldSamples (UnkownSet, lastCleanup);
        lastCleanup ← i;
    outputStream.append(sample);
```

Algorithm 1: Our interpretation of MINAS [7]

The Novelty Detection function, illustrated in Algorithm 2 groups the instances to form new clusters and each new cluster is validated to discard the non-cohesive or unrepresentative ones. Valid clusters are analyzed to decide if they represent an extension of a known pattern or a completely new pattern. In both cases, the model absorbs the valid clusters and starts using them to classify new instances.

```
Parameters: minExamplesPerCluster, noveltyFactor
Function NoveltyDetection(Model, Unknowns):
    newModelSet ← ∅;
    foreach cl in clustering (Unknowns) do
        if | cl.sampleSet | ≥ minExamplesPerCluster then
            (distance, near) ← nearestCluster (cl, Model);
            if distance < near.radius × noveltyFactor then
                cl.label ← near.label;
                cl.type ← extension;
            else
                cl.label ← noveltyIndex;
                noveltyIndex ← noveltyIndex +1;
                cl.type ← novelty;
            Unknowns ← Unknowns − cl.sampleSet;
            newModelSet ← newModelSet ∪ cl;
    return newModelSet;
```

Algorithm 2: MINAS [7] Novelty Detection task.

3 Proposal

In this work we investigate an appropriate architecture for performing DSND at the edge, as a means of allowing small IoT devices to filter detect undesirable network behavior. Our approach is based on the IDSA-IoT architecture [3] and DSND techniques provide by the MINAS algorithm [7]. Named *MFOG*, our distributed algorithm explores load balancing to enable low profile devices at the edge of the internet to also work on the classification and detection of unwanted traffic.

In this work we propose and asses *MFOG*, a distributed data stream novelty detection system based on the algorithm MINAS for securing IoT networks. *MFOG* implements a distributed version of MINAS according to the IDSA-IoT architecture proposed in a previous work [3], to execute in the edge where small devices and constrained resources may be prevalent.

However, given the distributed nature and the typical use of small computing devices in IoT scenarios, new challenges arise: (*i*) the classification phase of the algorithm must occur in parallel at different nodes; (*ii*) the novelty detection phase, which provides the model evolution, must also be asynchronous; (*iii*) the algorithm complexity (time and space) must allow it to be processed by modest computing devices (i.e., small memory and low processor performance).

NIDS monitor network traffic, and analyze the characteristics of each flow to identify any intrusion or misbehavior. However, this problem requires both fast and accurate response [4]: fast response is needed to have a proper reaction before harm can be cast to the network and to cope with the traffic without imposing loss or delay in the NIDS or observed network; accurate response is required as to not misidentify, especially the case of false positive that leads to false alarms. To achieve those goals we leverage fog computing.

In common IoT scenarios, data is captured by small devices and sent to the cloud for any compute or storage tasks, but this is not feasible in a NIDS scenario. Fog computing infrastructure aims to offload processing from cloud providers by placing edge devices closer to end-users and/or data sources.

In our proposal, fog and cloud computing resources are combined to minimize the time elapsed between a flow descriptor ingestion and intrusion alarm, performing the classification step of MINAS in an MPI cluster running multiple classifier instances. After the initial classification, the resulting label can be used immediately, but if the sample is labeled as *unknown*, this sample must be stored and the novelty detection step will be triggered.

To have a better overview of our proposal and how it integrates with existing IoT environments, Figure 1 depicts such scenario showing from bottom to top: IoT devices directly connected to a (local) gateway network; this gateway network could be as simple as a single Internet router or be more complex by connecting to private clouds or containing more devices providing fog computing capabilities; lastly, available over the internet, traditional public cloud provides inexpensive computing and storage on demand. In this scenario the further apart resources are, more network resources need to be employed and, as with any networked system, the higher is the latency.

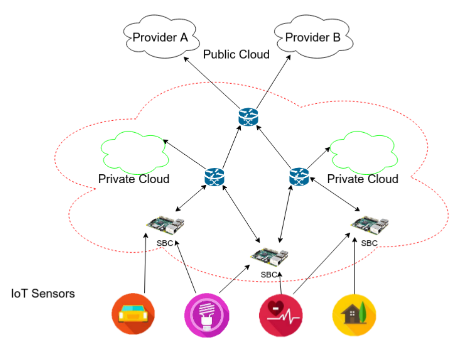


Fig. 1: IDSA-IoT [3] physical architecture and deployment scenario overview.

The overall *MFOG* architecture has two main modules, Classification and Novelty Detection, handling MINAS main tasks. The Classification Module performs the same task of the MINAS Online phase and is the focal point for parallelism and distribution in our proposal. It is replicated in the fog, and runs

```
Parameters: cleaningWindow, noveltyDetectionTrigger, mpiClusterSize as
  mpiSize, mpiNodeRank as mpiRank
Input: ModelSet, Sample Stream
Output: Classified Stream as out
Function Mfog(ModelStream, InputStream):
  ModelSet = ∅;
  ModelSetLock = new Lock ();
  if mpiRank == 0 then root
    new Thread (Detector, [ModelSet]);
    Sampler (InputStream);
  else leaf
    new Thread (modelReceiver, [ModelSet]);
    Classifier (ModelSet);
```

Algorithm 3: MFOG: main MPI entry-point.

on each cluster node, using a configurable number of threads (limited to the node CPU core count).

The Novelty Detection Module can be also replicated, the choice being one instance per local network, one global cloud instance, or both. This module also handles the homonymous task of MINAS Online phase, receiving all the samples labeled with *unknown*, storing them in a internal *unknown-buffer*, and, when this buffer is full, performing the MINAS Novelty Detection task (clustering followed by validation).

3.1 Polices

The design of our distributed DSND architecture includes partitioning the functionalities of MINAS and establishing the appropriate data flows between different actors. Changes to placement and behavior can have different impacts and should be chosen with care. The decisions following these discussions can be organized in several policies, some of them were recurring during our implementation discussions and are:

– Regarding the allocation of the Novelty Detection Module:
  - At each fog node: patterns will be only detected if sufficient samples of them occur in the local observed network, use of the local node processing power and, a model synchronization mechanism between networks must be added;
  - In the cloud: detect patterns even when scattered on each local network, each sample with *unknown* label must be sent from edge to cloud implying increased internet link usage and increased delay between the appearance of a pattern, its detection and propagation to fog classifiers;
  - On both: local *unknown* buffer is maintained and novelty detection is local as well, once a sample is considered as noise or outlier it shall be sent to the cloud where the process repeats but with global data. This choice needs a even more complex a model synchronization mechanism.

```
Function Classifier(mp):
  while True do
    sampe = receive (SampleType, root);
    if sample == EndOfStream then break;
    sample.label = unknown;
    with readLock (ModelSetLock)
      (distance, cluster) = nearestCluster (sample, ModelSet);
    if distance < cluster.radius then
      sample.label = cluster.label;
    send (root, SampleType, sample);
Function modelReceiver(mp, ModelSet):
  while True do
    cl = receive (ClusterType, root);
    if cl == EndOfStream then break;
    with writeLock(ModelSetLock)
      ModelSet = ModelSet ∪ cl;
```

Algorithm 4: MFOG Leaf Tasks: Model Receiver and Classifier.

– Regarding the model cleanup (forget mechanism): Even when a global novelty detection is used, local models can be optimized for faster classification using the local model statistics by sorting by (or removing) least used clusters;
– Lastly, reclassification of *unknowns*: In the novelty detection task in MINAS, the *unknown* sample buffer is effectively classified using the new set of clusters. In Algorithm 2, at line 13, the new cluster valid (novelty or extension) includes the set of samples composing that cluster, thus, if this new label assignment was put forth to the system output it would introduce delayed outputs, more recent and perhaps more accurate. Also, it would change the system data stream behavior from a *map* (meaning each input has one output) to a *flatMap* (each input can have many outputs).

3.2 Implementation

The original MINAS algorithm has a companion unpublished implementation (*Ref*) written in Java using MOA library base algorithms such as K-means and CluStream, but our implementation only used K-means. Another difference between *Ref* and *MFOG* is the calculus of the cluster radius from the distances of elements forming the cluster and the cluster's center. *Ref* uses the maximum distance while *MFOG* uses the standard deviation of all distances as described in [7].

The stream formats for input and output are also of note. As input, the algorithm takes samples ($\vec{v}$), which are a sequence of numbers with dimension d. In addition to $\vec{v}$, for both training and evaluation, the class identifier is provided as a single character, along with an unique item identifier (*uid*), which can otherwise be determined from the sample index in the stream.

```
Function Sampler(mp, p, InputStream):
  dest = 1;
  foreach sample from InputStream do
    if typeOf (sample) is Cluster then
      broadcast (ClusterType, sample, root);
      with writeLock (ModelSetLock)
        ModelSet = ModelSet ∪ sample;
      continue;
    send (dest, SampleType, sample);
    dest = dest +1;
    if dest > mpiSize then dest = 1;
Function Detector(mp, ModelSet):
  lastCleanup = while True do
    sampe = receive (SampleType, any);
    if sample == EndOfStream then break;
    out ← sample;
    if sample.label == unknown then
      UnkownSet = UnkownSet ∪ sample;
      if sizeOf (UnkownSet) ≥ NDT then
        novelties = NoveltyDetection (p, ModelSet, *UnkownSet);
        with writeLock (ModelSetLock)
          ModelSet = ModelSet ∪ novelties;
        foreach cl in novelties do
          broadcast (ClusterType, cl, root);
      if now () > lastCleanup + CW then
        ModelSet = handleModelSleep (ModelSet, ModelSleepSet);
        UnkownSet = removeOldSamples (UnkownSet, lastCleanup);
```

Algorithm 5: MFOG Root Tasks: Sampler and Detector.

As its output, the algorithm returns the original sample $\vec{v}$ followed by the assigned label. Adjustments can easily be made to provide the output results as a tuple containing *uid* and the assigned label.

For evaluation purposes, an *MFOG* implementation was made using MPI (*Open MPI 4.0.4*). The program is organized in an SPMD programming model, so a single version of the *MFOG* program was initiated on all nodes, being that one of them would perform the root role, while the others ran as leafs. On the root process, a sampler thread is responsible for distributing the sampled flow information ($\vec{v}$) to the classifier nodes, using a round-robin load balancing scheme. The other thread on the root process is responsible for receiving the classification results and for processing the unknown samples in search for novelties. Each leaf node runs a model adjustment thread and multiple (up to the number of cores) classifier threads.

The overall sequence of interactions is shown in Figure 2.

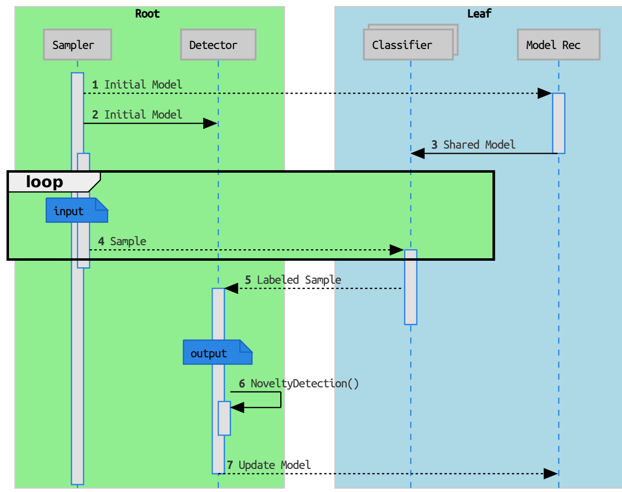


Fig. 2: *MFOG* life line overview.

4 Experiments and Results

For the experimental setup we dedicated three Raspberry Pi 3 model B single board computers connected via Ethernet Switch forming a simple cluster. This cluster stored all source code, binaries (compiled and linked in place) and datasets, being accessed via our laboratory network over Secure Shell (SSH). All experiments were executed in this cluster for isolation of otherwise unforeseen variations.

The dataset used is the December 2015 segment of Kyoto 2006+ Dataset[1] (Traffic Data from Kyoto University's Honeypots) [14]. This segment was filtered (from 7 865 245 instances) to contain only examples associated to known attack types identified by existing NIDS, and attack types with more than 10 000 instances for significance, as previously done by [3]. The remaining instances then were transformed by normalization so each feature value space (e.g. IP Address, Duration, Service) is translated to the Real interval $[0, 1]$.

The resulting derived dataset is then stored in two sets, training set and test set, using the holdout technique. However, for the training set we filter in only normal class resulting in 72 000 instances. For the test set we use 653 457 instances with 206 278 instances with "N" (normal) class and 447 179 instances with "A" (attack) class. Note that this choice results in a possible overfitting for the normal class and, under-fitting for the attack class as the system first needs to detect a novel class and then add it to the model.

[1] Available at `http://www.takakura.com/Kyoto_data/`

4.1 Measures and Visualizations

There are two broad evaluation measures for each experiment: a time measure extracted by using *GNU Time 1.9* measuring of the full program execution and, a set of qualitative measures extracted by a Python program.

Our evaluation script was build following reference techniques like multi-class confusion matrix with label-class association [7] to extract classification quality measures. This program takes two inputs, the test dataset and the captured output stream, and outputs the confusion matrix, label-class association, final quality summary with: Hits (true positive), Misses (Err), Unknowns (UnkR); and stream visualization chart with per example instance summary with novelty label markers. For clarity, it is necessary to detail how to interpret and compare each measure, as for some it is trivial but others are not so much.

In the confusion matrix $M = m_{ij} \in \mathbb{N}^{c \times l}$, computed by our evaluation program, each row denotes one of the datasets original (actual) class c and each column denotes the marked (predicted) label l present in the captured output stream. Thus, each cell $M_{c,l}$ contains the count of examples from the test dataset of class c found in the output stream with the label l assigned by the under evaluation experiment.

For the dataset under use, original classes are $c \in \{N, A\}$, and for the labels we have the training class *"N"*, *unknown* label *"-"* and the novelties $i \in \mathbb{N}$ so $l \in \{N, -\} \cup \mathbb{N}$.

Added to the original confusion matrix C are the rows *Assigned* and *Hits*. *Assigned* row represents which original class c (or if *unknown*, *"-"*) the label l is assigned to, this is computed by using the original class if $c = l$ or by associated novelty label to original class as described in [6] section 4.1 (class from where the most samples came from). *Hits* row shows the true positive count for each label, computed by coping the value of the cell $M_{c,l}$ where the label is the same and the class c is the value in the above *Assigned* row. The *Hits* row is also used to compute the overall true positive. One complete matrix is shown in Tab. 1a.

For the measure summary table, six measures from two sources are displayed. Three measures *Hits*, *Unknowns* and *Misses* represented as ratio of the captured output stream, extracted from the evaluation python program, computed as follows: *Hits* (true positive rate) is the sum of the *Hits* row in the extended confusion matrix; *Unknowns* is the count of examples in the captured output stream marked with the *unknown* label (*"-"*); *Misses* is the count of all examples in the captured output stream marked with a label distinct from the *Assigned* original class and are not marked as unknown.

Furthermore in the measure summary table, *Time*, *System* and *Elapsed* measures represented in seconds, are extracted from *GNU Time*. *Time* is the amount of CPU seconds expended in user-mode (indicates time used doing CPU intensive computing, e.g. math); *System* is the amount of CPU seconds expended in kernel-mode (for our case it indicates time doing input or output); *Elapsed* is the real-world (wall clock) elapsed time and indicates how long another system or person had to wait for the result. To compare the time measure is simple, the lower time taken, the better. Our four main experiments are shown in Tab. 2.

Table 1: Confusion Matrixs and Qualitative measures

(a) Reference implementation

Labels	-	N	1	2	3	4	5	6	7	8	9	10	11	12
Classes														
A	3774	438750	123	145	368	8	52	165	1	1046	161	2489	71	26
N	8206	193030	0	79	44	0	0	0	229	181	154	4066	289	0
Assigned	-	N	A	A	A	A	A	A	N	A	A	N	N	A
Hits	0	193030	123	145	368	8	52	165	229	1046	161	4066	289	26

(b) Serial implementation

Labels	-	N	0	1	2	4	5	6	7	8	10
Classes											
A	16086	429765	94	995	104	0	23	3	29	46	34
N	12481	193642	3	94	0	47	0	0	0	11	0
Assigned	-	N	A	A	A	N	A	A	A	A	A
Hits	0	193642	94	995	104	47	23	3	29	46	34

(c) Parallel single-node

Labels	-	N	0	1	2	3	4
Classes							
A	12282	433797	147	952	0	0	1
N	3088	203019	40	99	27	5	0
Assigned	-	N	A	A	N	N	A
Hits	0	203019	147	952	27	5	1

(d) Parallel multi-node

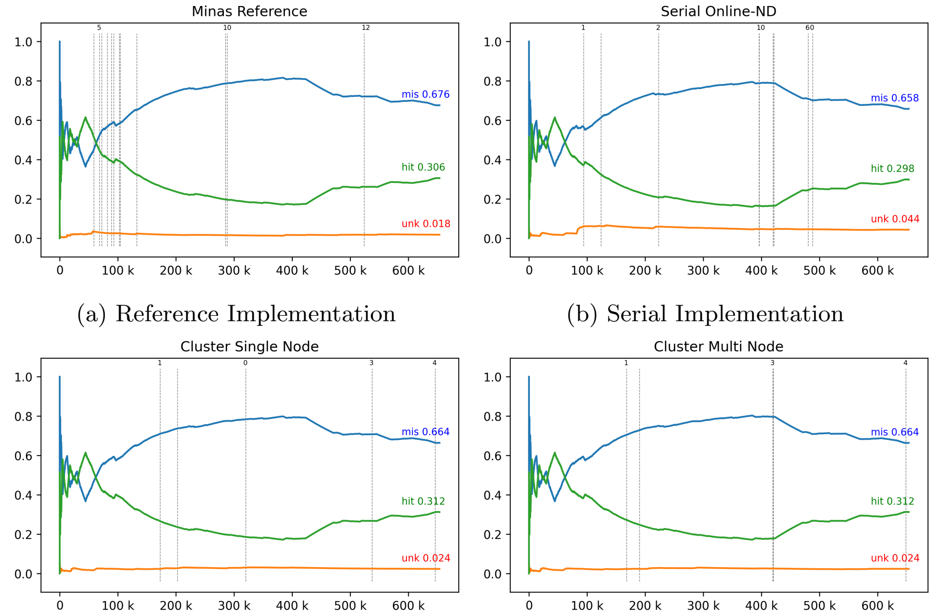
Labels	-	N	0	1	2	3	4
Classes							
A	12378	433631	117	886	0	162	5
N	3121	202916	40	96	105	0	0
Assigned	-	N	A	A	N	A	A
Hits	0	202916	117	886	105	162	5

Lastly, the stream visualization chart shows the summary quality measure (*Hits*, *Unknowns*, *Misses*) computed for each example in the captured output stream. This summary is computed for each example but it uses the *Assigned* row computed previously to evaluate *Hits*, other measures are derived as described before. Horizontal axis (x, domain) plots the index of the example and the vertical axis (y, image) shows the measure computed until that example index on the captured output stream.

Adding to the stream visualization chart, novelty label markers are represented as vertical lines indicating *when* in the captured output stream a new label first appeared. Some of the novelty label markers include the label itself ($l \in \mathbb{N}$) for reference (showing every label would turn this feature unreadable due to overlapping). Figure 3 shows complete stream visualization charts.

4.2 Results Discussion

Four main experiments need detailed discussion: (a) reference implementation of Minas (*Ref*) [7]; (b) new implementation in serial mode; (c) new implementa-



(a) Reference Implementation (b) Serial Implementation

(c) Parallel single-node (d) Parallel multi-node

Fig. 3: Stream hits and novelties visualization

tion in single-node, multi-task mode and (d) new implementation in multi-node, multi-task mode. Each experiment uses the adequate binary executable, initial model (or training set for the reference implementation) and test set to compute a resulting output stream which is stored for qualitative evaluation. The summary of all four experiments is shown in Table 2.

The comparison of the first two experiments (a and b) does serve as validation for our implementation, while the latter three (b, c and d) serves as showcase for the effects of distribution.

As stated, to validate our implementation we compare it to *Ref* (the original MINAS companion implementation), so we extracted the same measures using same process for both a and b, they can be viewed on Tables 1a, 1b and for ease of comparison on Table 2 the summary can be compared side by side.

In general, the observed classification quality measures are very similar, they diverge slightly where a has more *Hits* and *Misses* whereas b shifted those to *Unknowns*. This phenomenon was watched very closely during development and we found that small changes to MINAS parameters, MINAS internals like K-means ordering, cluster edge inclusion and cluster radius formula as stated in Subsection 3.2.

As for the time measures on Table 2 our implementation used less time to analyze the test data set. This is mostly due to the stop condition on the internal K-means algorithm, while *Ref* uses a fixed iteration limit of 100, our implemen-

Table 2: Collected Measures Summary.

	Ref (a)	Offline	Serial (b)	Single Node (c)	Multi Node (d)
Hits	199708		195017	204151	204191
	0.305618		0.298438	0.312416	0.312478
Misses	441769		429873	433936	433767
	0.676049		0.657843	0.664061	0.663802
Unknowns	11980		28567	15370	15499
	0.018333		0.043717	0.023521	0.023718
Time	2761.83	194.12	80.79000	522.1000	207.1400
System	7.15	0.075	11.51000	47.7700	157.6100
Elapsed	2772.07	194.27	93.03000	145.0400	95.3800

tations adds the “no improvement” check and stops earlier on most cases and this in turn reduces time taken on the *NoveltyDetection* function. There are also small optimizations on the *nearestCluster* function (minimal distance from sample to cluster center in the set) affecting the *classifier* task and *NoveltyDetection* function. Also note that *Ref* time in a includes the Offline phase while our implementation runs it once and reuses the initial model for b, c and d, in the table the offline time is on its separated column.

As for the effects of running a MPI cluster with our implementation we observe an increase of time when e go from 2 to 4 instances in a single node (b and c respectively), hinting that our choice of load distribution is not as effective as we expected. Further experiments were conducted with instances varying from 1 (serial) to 12 (3 nodes with 4 CPUs each) and true positive rate (*Hits*) and elapsed time had no major difference. More detailed time measurements can be seen on Figure 4, where we observe near constant time for *elapsed* (near $100s$), the *system* increases gradually while *user* decreases at the same rate. We interpret this behavior as a display of potential for gains using a better load balancing than our choice of round-robin such as micro-batching for better compute-to-communication ratio (CCR). In general Figure 4 shows no speedup but also no penalty for scaling to more than 4 instances.

Nevertheless, we can also show the effects of delay in the Classify, Novelty Detection, Model Update and Classify feedback loop. Comparing b and c we observe a reduction in Novelty labels on the Confusion Matrix (tabs. 1b and 1c) from 10 to 4. The same effect is observed on the stream visualization (figs. 3b and 3c) where our serial implementation has less novelty markers and they appear latter, but the measures keeps the same “shape”. Comparing c and d the difference is even smaller, (figs. 3b and 3c) as they both suffer the expected delay in the feedback loop.

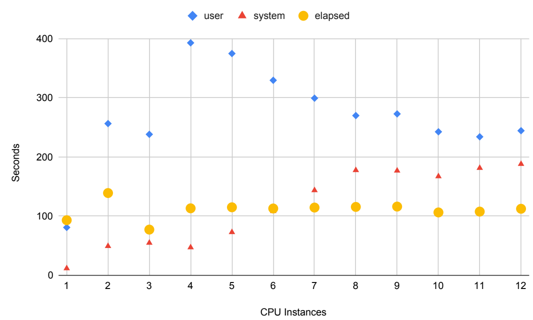


Fig. 4: Time measurements per added instance

5 Conclusion

Novelty Detection in Data Streams (DSND) can be a useful mechanism for Network Intrusion Detection (NIDS) in IoT environments. It can also serve for other related application of DSND using continuous network or system behavior monitoring and analysis. such maintenance tasks. Regarding the tremendous amount of data that must be processed in the flow analysis for DSND, it is relevant that this processing takes place at the edge of the network. However, one relevant shortcoming of the IoT in this case is the reduced processing capacity of such devices.

In this sense, we have put together and evaluated a distributed architecture for DSND at the network edge.

In that small computing on edge scenario, we propose *MFOG*: a distributed DSND implementation based on the DSND algorithm MINAS, and, evaluated with a NIDS task with appropriate dataset. The main goal this work to observe the effects of our approach to a previously serial only algorithm, specially in regards to time and quality metrics.

While there is some impact on the predictive metrics this is not reflected on overall classification quality metrics indicating that distribution of MINAS shows a negligible loss of accuracy. In regards of time and scale, our distributed executions used less time than previous implementation but efficient distribution was not achieved as the observed time as we added nodes remained constant.

Our treatment involved reworking the algorithm and implementation to be distributed and to minimize the memory usage as to fit in smaller devices. Other algorithms still need a similar treatment and, more importantly, other distribution strategies should be considered.

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