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# A Lightweight System for Just-In-Time Aggregation of Machine Generated Data in a Distributed Network

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**Abstract.** Application Data Management or ADM is a research area concerned with the aggregation, storage and presentation of information typically emitted from Enterprise Applications. ADM is a subset of Enterprise Information Management or EIM [27]. EIM usually joins together Business Intelligence and raw Application Data. Large scale commercial EIM systems started to appear in 2003, and since then many of the larger software vendors such as Tibco, Oracle and SAP [28] have created their own systems. The goal of each system is to present the Machine Generated Data [17] or MGD being emitted from applications and servers. Over the past few years, there has been a focus in EIM on dealing with the challenge of Big-Data as companies such as Amazon, Facebook and Zynga generate terabytes of application information per day. This data, when organized, can be used in the analysis of system problems, user behavior and security threats.

## 1 Introduction

Application Data Management or ADM is a research area concerned with the aggregation, storage and presentation of information typically emitted from Enterprise Applications. ADM is a subset of Enterprise Information Management or EIM [27]. EIM usually joins together Business Intelligence and raw Application Data. Large scale commercial EIM systems started to appear in 2003, and since then many of the larger software vendors such as Tibco, Oracle and SAP [28] have created their own systems. The goal of each system is to present the Machine Generated Data [17] or MGD being emitted from applications and servers. Over the past few years, there has been a focus in EIM on dealing with the challenge of Big-Data as companies such as Amazon, Facebook and Zynga generate terabytes of application information per day. This data, when organized, can be used in the analysis of system problems, user behavior and security threats.

Most EIM software solutions work in either an Active, Passive or Combined operation mode. An Active system requires installation of modules or agents (sometimes called collectors) on servers which are being monitored. The agents usually run with a relatively high level of access and feed information back to a central aggregator. The agents can very efficiently pass the information back to the server and have extremely fast access to the data. A Passive system on

the other hand operates entirely remotely and must work harder to retrieve and analyze the data. Typically, file and directory access will need to be granted to the host system by an Administrator over a particular protocol but software is not required to be installed once access has been granted. For the purposes of this dissertation we will focus on the Passive style. The major challenges for all EIM systems are

1. Accessing and Transmitting Data
2. Indexing Data
3. Searching Data

Data access is the most straight forward issue to solve in both the Passive and Active style as Administrators must be involved in either solution or need to at least provide some level of configuration. Data indexing and Searching however are much more difficult to solve for and as such typically involve mathematical solutions (such as Bloom Filters[22,23] for instance) to resolve. This dissertation will attempt to design a lightweight Passive analysis system which can be used to quickly aggregate and view short term data within a system, rather than detailed historical analysis. Such a system could be used to quickly analyze application issues during a high severity event within an Enterprise.

This system would have several advantages over existing software

1. A Light installation foot print (1 server)
2. Low overall network utilization
3. Low overall CPU usage on server and monitored host

## 2 Background and related work

In this section we will outline modern approaches to data aggregation and analysis of Machine Generated Data. This area has seen considerable innovation over the past 10 years and so there are many methods being used. Many of the systems use proprietary technology and granted patents [24]

In this section we will outline modern approaches to data aggregation and analysis of Machine Generated and JVM based Data.

### 2.1 Distributed Data Collection methods

Information from Enterprise Applications is typically stored in log files on the disks of servers running these applications. The servers may be running a variety of Unix, Linux or Windows based operating systems.

Each server typically stores application logs in a variety of different areas on disk depending on how the application was developed. In addition to the application logs themselves, the software used to run the application may also have logs, and errors can be reported in any one of these files. Logs break down into several categories:

a) Be-spoke Application logs (Developer created);
b) Off-the-shelf Application Software Logs (Apache, Weblogic, Tomcat);
c) Logs generated from the RunTime Environment for example JVM based logs (In Java environments);
d) Logs generated by the Operating system.

In active EIM systems collection of this data is usually performed by Agents and centrally forwarded to a Log Aggregation server where it can be searched. In highly secured environments with change management concerns, a Passive approach is preferable where a centralized logging server pulls data from each server using common protocols and aggregates it afterwards.

### 2.2 Active Analysis (Push)

Compared to systems which do not require custom client software installation, Active Analysis systems typically require a large amount of setup,design and configuration, requiring Agents to be installed on the operating system which is running the monitored application. The system must then be configured to read and forward information to a central location where it is collated for presentation. Agents usually forward data over a network port (UDP/TCP or HTTPS) to the central aggregator. This method of collection is the very efficient as the agents have direct access to the data under analysis. This method also scales as the number of nodes under management increases. This is due to the fact that the client machines are running some of the required software, and as such the CPU usage required to retrieve the data from them is more evenly distributed.

### 2.3 Passive Analysis (Pull)

Passive Analysis systems typically require less setup and design, with more or less the same amount of configuration as Active systems. One or more central servers are installed on the network and they are configured to remotely read the logs of the monitored application. Drawbacks of this approach are that it is less efficient than having direct disk access to the files in question. The reason for this is that active analysis systems can more easily be configured to filter on certain events and feed the central server when these events occur, passive systems must analyze the data once it has been retrieved, and then decide which data to keep. Also, as it uses existing operating system software (such as SSH) to make connections to remote machines, it is also highly dependent on the operating system under analysis.

### 2.4 Machine Generated Data

This article [10], created relatively recently (Dec 2010) describes machine generated data as information automatically created from a computer process, application, or other machine without the intervention of a human. This statement is of course partially true, and is acknowledged as such, due to the fact that

information generated by processes or machines is inherently tied to the humans which are interacting with it or issuing commands to the system.

It is more accurately described by Monash [17], in a provisional definition, as information that was produced entirely by machines OR data that is more about observing humans than recording their choices. The article goes on to further describe the categories under which MGD falls, such as the output of network, telemetry and other computer equipment appliances.

The text also categorizes MGD as information which can be, and probably should be, frequently discarded. This statement fits with the purpose of this dissertation, which is to develop a method to quickly review, but not store MGD in a sliding window fashion.

### 2.5 Available Data Collection and Aggregation Systems

GrayLog2 [1] is an open sourced centralized logging system intended for use by organizations in order to provide a window onto real-time and historical log data. The data is pushed to Graylogs server (graylog-server) using syslog from each registered node in data pipelines known as streams. The nodes themselves must be registered within GrayLog using its UI interface. Gray log records the Date, Host, and Level of each of the incoming messages. It reports the number of message per second which are coming into the system in the UI. It has advanced searching features using Elastic Search as its backend, which even allows some natural language to be used when searching records (i.e you can search a Timeframe such as from yesterday). This UI also provides advanced graphing and tracking of multiple sources at once. It does not support a centralized Multi-SSH server siphon as outlined in the dissertation.

LogStash [5] is also an open sourced tool for managing events and logs. It is written in Ruby and runs on a Java runtime using JRuby. Again with LogStash it uses a push model in order to Ship events from each node to Brokers which cache the information for the Indexers so that they do not become overloaded, this is then finally redirected to the Storage and Search server that is accessible via a Web UI. LogStash has a highly configurable UI (utilizing Kibana) which allows you to create your own dashboards for your application. LogStash needs to be installed on the nodes which contain the logs if they are not being presented over the standard Syslog port 514. [19]

OpenTSDB [2] provides another way to push log and metrics events to a central location. It is a highly scalable system which is in use by many companies [3] at the time of writing. The base components for the system is the Time Series Daemon or TSD, several of which is installed on the network being monitored. Each TSD uses HBase [4] to store and retrieve data. Collectors, which are basically scripts that are scheduled to run on each monitored node, send data to each TSD which in turn writes the data to HBase. Each monitored node must be aware of the TSDs on the network so that it can send data to them. Again, OpenTSDB is mainly is focused on aggregation and storage of large amounts of historical data and at massive scale, so it utilizes the common

push method to achieve this. From a UI perspective, OpenTSDB provides only basic functionality [6] when compared to Kibana based solutions.

Apache Flume [20] is a distributed, reliable, and available service for efficiently collecting, aggregating, and moving large amounts of streaming event data. Everything in Flume is defined in the content of an event. Events are transported, routed and stored by Flume Agents. Flume Agents are a collection of Flume Sources, Sinks and Channels, Sources can poll or wait for events, Sinks allow the data to be streamed to a destination (i.e HDFS), and channels provide the conduit between the Source and the Sink (i.e the Source sends the events to a Channel and the Sink drains the Channel).

There are no SSH connectors for Flume (although open source attempts [7] have been contributed), the reason for this is that the default solution for reading data is to install agents on the Application Server obtaining the logs and to send them to a Sink. The output of this dissertation project is to build a completely passive SSH spooling service that can be connected to a data source, so it is possible that it could be made compatible with Flume.

Splunk [21] is a closed-source commercial offering which is in use by thousands of customers worldwide. It is available in both free and enterprise edition(s). Splunk uses an architecture whereby a Forwarder sends data to a Splunk Indexer, a separate server known as the Splunk Search Head provides a UI by which to search the Indexer(s) for event data. It follows paradigms which are very similar to that of OpenTSDB and Flume but with a much richer UI and a simplified configuration. Splunk also scales horizontally extrmnely well Splunk does not provide a feature to read remote files via SSH, if you wish to do so, a script needs to be written to connect to the SSH server and then forward the data.

Kafka [22] is a newer data collection system which was not mentioned in the original proposal, at the time it was at viewed as being so similar to Flume that only one of them merited deeper analysis. It was also at version 0.7.0 having not been released from the Apache Incubator after it was contributed in 2011. Today, Kafka is one of the leading real time open source data pipelines. LinkedIn also released a companion paper [9] which describes the entire system in detail. Kafka is also horizontally scalable and supports up to 40 billion events per day at LinkedIn. [10]

Kafka uses the notion of a Producer and Consumer which send a retrieve data respectively from a Kafka cluster of Brokers. Kafka also has the concept of a channel (similar to Flume) on which you send data to Brokers which is called a Topic. Kafka is very much the just mechanism for achieving data collection at Scale, it does not provide any default Producers or Consumers, these must be written. An example of a simple tail Producer [11] is available on GitHub. Apache Storm [12] is frequently used with Kafka as a distributed computation engine which operates on data streamed from a Kafka cluster.

Suro is a data pipeline in use by both NetFlix and Riot Games [14, 13]. Suro is a collection and storage mechanism for streaming data. The version of Suro in use by Riot Games is closed source and known as Honu, but is similar in operation to the version of Suro recently open sourced by NetFlix, they were

both developed by the same author independently for both companies. Suro uses a pure collect and forward architecture, requiring Collectors to be installed close to the application being monitored. Agents are not required to be installed on the monitored nodes, however any application which needs to send data to Suro needs to implement SuroSDK, which effectively generates a client side dependency. You cannot use Suro to SSH or retrieve data from nodes remotely. However, it would be possible to implement Suro support into the Multi-SSH server such that it provided its output to Suro. Suro can forward raw data to either S3 or Kafka for further processing. It does not have a real-time consume library or mechanism, hence the use of Kafka.

## 3 Problem Description

As stated in section 2, EIM systems typically fall into two categories of implementation, Active and Passive. One of the problems with an Active system is that it requires significant setup time and continued involvement with a Systems Administration group for upgrade of agents and application of security fixes to same. Some EIM systems do not even allow a remote collection option without first installing software on the host machine.

The other issue with existing EIM systems is that they may not focus on one particular problem but in fact solve for every possible scenario, which sometimes dilutes features which would otherwise be useful.

Existing EIM systems are largely focused on retrieving value from, and analyzing data across, the entire organization, continually. This generates huge amounts of data which may, or may not be useful.

In certain scenarios, only data over a very short time frame is actually useful, and required to solve the problem. Once this data has been obtained and a solution has been determined, its value steadily decreases.

An example Scenario is detailed below.

### 3.1 IT Crisis Management

A typical IT crisis support scenario requires an engineer to log into and analyze logs from several different sources at once. The data under analysis does not always follow a pattern and the problem may only be apparent to the engineer observing the data. Also the issue in question may involve discovering a pattern that is across several logs, residing at several separate network locations before a solution may be suggested.

Engineers typically have access to these systems for the purposes of deciphering these problems, but there are few tools, if any, which can be easily setup to analyze data using their existing credentials.

The engineer requires visual access to the following information

- Time ordered log information from all sources
- Methods to blend this data together to discover a pattern
- Methods to visualize errors within the data

### 3.2 Proposed Solution

I propose a system which can quickly attach and siphon data from a system during a crisis management situation and allow an engineer to assess the state of the application and suggest solutions very quickly.

The system would attach itself to machines through standard protocols, (primarily SSH2 on Unix) and make data requests using standard shell commands. This data would be made available to a Rich UI (such as Flex or ExtJS) using a REST API.

The proposed system would have the following characteristics

- Lightweight Client (Web Based Interface on Rails or PHP)
- Lightweight Server (Multi SSH2 client at the core)
- Client would be a live dashboard of log information and performance data
- Applications and their underlying infrastructure and data files are defined in profiles
- Minimum Indexing Features  not required as data volume is very low (in comparison to commercial offerings)
- No real historical data  Only real-time (plus or minus X hours)
- Crisis Event export features (i.e a Snapshot of what was logged and how systems were performing during the event)
- The system would operate in a standby or active mode
- Standby mode is where the system is connected via SSH2 to all servers within a particular Applications profile but is not pulling data.
- Active mode is where data is being pulled into memory for analysis and indexing, and as such the dashboard can now be connected to view data.
- The system would have large heap (or general memory requirements) but low disk space or archiving requirements (i.e up to 2GB overflow to disk)
- Disk access would only be required if the user shifts to a window which is no longer in memory.

# 4 Passive MGD Collector Design

The Multi-SSH client system involves design and development of the following components

- Passive MGD Collector (or DSS)
- DSS Data Model
- DSS UI

The purposes of this document will be to describe the technical design proposal for the components above.

## 4.1 General Architecture and Problem Domain Model

The basic operation of the system is to download machine generated data from several hosts at once via SSH and feed them onto a queue where they can be consumed and presented in a UI.

The MGD being retrieved should normally represent a holistic view of an application or system (such as all of the security logs across an entire server farm)

Before this can be achieved, the hosts, applications and logs must all be predefined in a database so that they can be retrieved quickly and siphoned into the UI on a just in time basis.

The Architecture consists of the following components

- Data Siphon Server :: input-filter
- Data Siphon Server :: multi-ssh-client
- Data Siphon Server :: output-filter
- Data Siphon Server :: queueing-system
- Data Siphon Server :: app-database
- Data Siphon Server :: profile-manager

- UI Server :: rest-data-access
- UI Server :: queue-reader
- UI Server :: ui-dashboard

The problem domain consists of the following entities.

- Applications (Web, Daemons)
- Nodes (Hosts, Servers)
- Machine Generated Data Points (Logs)

These components are described in more detail in the diagram below and also in the next section.

## 4.2 Data Siphon Server Component

In this section we will analyze the different components of the system and determine suitable software designs and libraries to be used.

**multi-ssh-client** In order to connect and retrieve log information, across multiple servers, a client which can log into and maintain a very high number of SSH connections will need to be developed or obtained.

This client should have the following characteristics

- Lightweight
- SSH2 support
- Supports compression
- Wide cipher support

Due to the high number of required connections, SSH libraries which have various compression methods will be preferred. There are several libraries which can be used across multiple different languages.

Libraries available and being considered are listed below

Java Client Libraries

| Name | License | Link |
|---|---|---|
| Ganymed | BSD | http://www.ganymed.ethz.ch/ssh2 |
| JCraft | BSD | http://www.jcraft.com/jsch/ |
| SSHj | Apache | https://github.com/shikhar/sshj |
| Jaramiko Maverick | Commercial | https://www.javassh.com |
| J2SSH | MIT Style | http://www.lag.net/paramiko/java/ |

Ruby Client Libraries

| Name | License | Link |
|---|---|---|
| Net:SSH | MIT Style | http://net-ssh.rubyforge.org/ |
| Rye | MIT Style | https://github.com/delano/rye |

C Libraries

| Name | License | Link |
|---|---|---|
| Dancers Shell | GNU | http://www.netfort.gr.jp/~dancer/software/dsh.html.en |
| LibSSH | LGPLV2 | http://www.libssh.org/ |
| FLowSsh | Commercial | http://www.bitvise.com/flowssh |

Python Libraries

| Name | License | Link |
|---|---|---|
| Paramiko | MIT Style | http://www.lag.net/paramiko/ |
| Spur | MIT Style | https://pypi.python.org/pypi/spur |
| Fabric | MIT Style | http://docs.fabfile.org/en/0.9.1/ |
| PXSsh (part of PexSpect) | MIT Style | http://pexpect.sourceforge.net/pxssh.html |

Most libraries do not inherent cater for the management and retrieval of data across multiple connections at once, although Dancers Shell, Fabric and Rye do.

Library Selection

The selected library for the implementation will be JSch (Java Secure Channel) from JCraft. This library is pure Java and includes key features such as

- High Performance Enabled SSH/SCP [1]
- JZlib compression
- Variety of Cipher and Encryption options

As such this library has the largest majority of features from other available libraries. The only feature which JSch does not implement by default is the ability to maintain several concurrent connections and execute identical commands on each one. However, the ease of use of the library makes it much straight forward to implement such functionality.

**input-filter** The purpose of the input filter is to protect the downstream operating systems from restricted commands that are not required for the operation of the data siphoning operation. The only system known to sanitize these commands at the time of writing is Rye, which disables the usage of

- File globs. i.e ls*.rb
- Environment variables as arguments. i.e echo HOME
- Pipes and operators i.e [REMOVED]
- Backticks, i.e procs=‘ps aux‘

Any implementation of the input-filter should at least cover the scenarios covered by Rye.

**output-filter** The purpose of the output filter is to discard erroneous data which would otherwise be queued and displayed on the UI. All data passes through this filter and as such there may need to be many instances of this component.

The primary function of the output filter is twofold and should be configurable as follows

- Allow the removal any data which the user has specified in their profile. (i.e The removal of lines containing the word INFO)
- Allow only specific data to pass through (i.e lines only containing the word ERROR)

**queuing-system** A queuing system is required in order to architecturally decouple ingest of data from its consumption. The UI should be able to read and display events independently of the system receiving the. The queuing system which is most likely to be used will be a simple in memory solution which will spill over to disk when full. In order to preserve messages and queue them to the UI, a persistent ActiveMQ solution may also be used. Access to the queue will be provided via an API.

**profile-manager** A profile management system is necessary in order to store the applications which a user wishes to monitor. This will be implemented as part of the MySQL database for the SSH Multi-Client application. A user will be able to store profiles containing information about the following entities

- Environments (i.e Production, Test)
- Nodes (i,e Application Hosts such as an Application Server, Db Server)
- Applications (The software being monitored)

**ui-dashboard and search** Currently Kibana [15] is being investigated for use as a dashboard and ElasticSearch [16] for search capabilities of the data. These technologies are current in use by other streaming collection mechanisms such as GrayLog2.

### 4.3 Data Siphon Server Data Model

The Ocelli Server data model (Fig 1.) is designed to support both the Admninistration UI of Ocelli and the server side application. As such, it contains elements which serve both. The model is designed such that you can answer the following questions

- "I would like to view the file server.log across all nodes utilised by Application X in Environment Y"
- "Which applications exist in Environment Y"
- "How manay applications are there in the Environment Y"
- "Which Artifacts are available for viewing which belong to Application X"

Some of the key elements in the data mnodel are described below

**Access Key** An Access Key is used to securely retrieve Artifacts from a Node. Where supported, the model supports the storage of SSH2 keys but can also fall back to username/password combinations.

**Artifact** An artifact is a resource on a Node containing information of interest to a User. An artifact may be of several different types (for instance it may be a disk file on a Node), although for the purposes of the research document, only Log files on disk are considered.

**Environment** A software deployment environment, such as Development, Test or Production. One Node may exist in multiple environments (For instance, a machine which services both a development and a test environment). An Application may exist in many environments at once.

**Application** An application represents a piece of software which creates Artifacts of interest on a Node. For instance a Web Based Application may create 3 Artifacts, a debug log, an error log and an info log. An application can exist in multiple Environments.

**User** A user is described as a person logging into the system for the sole purpose of connecting to a logging session for a particular application.

**Profile** Each User has a Profile where they store Applications of interest. These Profiles are associated to this user only and cannot be shared.

## 5 Experimental Testbed

In order to determine the viaibility of ingesting and processing data into a single server, tests will be performed in two seperate environments

- A physical non virtualized network consisting of machines co-located in the same data center.
- A virtualized network in Amazon's EC2 infrastructure

### 5.1 Simulation Environments

**Data Center** The data center test environment consists of 2 physical locations in Los Angeles and 10 physical nodes. These nodes are all Dell R420 rack mounted servers with the standard specifications connected via a 100MB network. In each data center they are in the same rack. We will refer to the Eastern and Western locations as Alpha and Bravo respectively. The data centers are conneceted via an 800Mpbs link.

**Amazon EC2** The Amazon EC2 test will be at a much larger scale as there are more nodes available in the EC2 environment. The test environment consists of 100 m1.xlarge nodes, using Amazon's first generation M1 platform. The M3 generation would have provided better performance at a lower price point, however these nodes were unavailable in the test environment.

Specifications for the m1.xlarge are listed below

| Attrubute | Value |
|---|---|
| Max Network Bandwidth | 40 Mb/s |
| CPU's | 2 Core (6.5 ECU) |
| Memory | 7.5 GB |

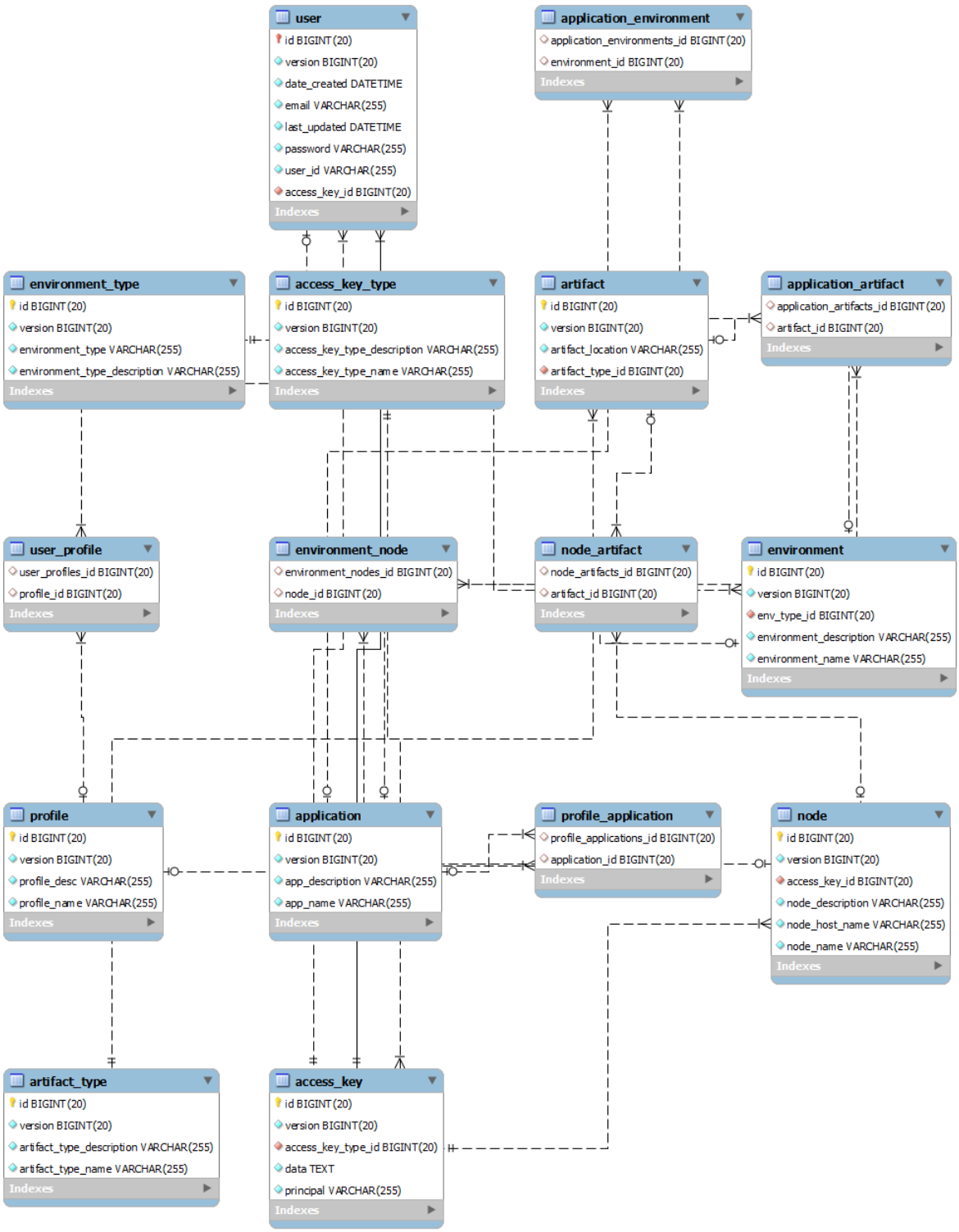



**Fig. 1.** Ocelli Server Data Model

### 5.2 Simulation Approach and Setup

Each test will consist of the following steps

- Load Ocelli Server Application UI
- Select Application in Ocelli Server UI
- Select Artifact to stream to Elastic Search
- Begin Streaming

After these steps have been taken Ocelli Server will connect to every node containing the artifiact, begin reading from the end of the file, and then start pushing the data to the Elastic Search cluster. The data will then be available for inspection.

**Requirements and Test Setup** The following are pre-requisites to performing a test run

- A User exists and is registered with Ocelli Server
- A User has a Profile Created
- The User has added an Application to their Profile
- All Nodes to be Monitored are registered with Ocelli Server (This will be performed via an SQL Script)
- An Artifact exists on all Nodes and is registered with Ocelli Server (This will be performed via an SQL Script)
- Each Artifact is a 2 GB Log File in /var/log/test.log
- The Elastic Search Cluster is empty and Indexes have been cleared

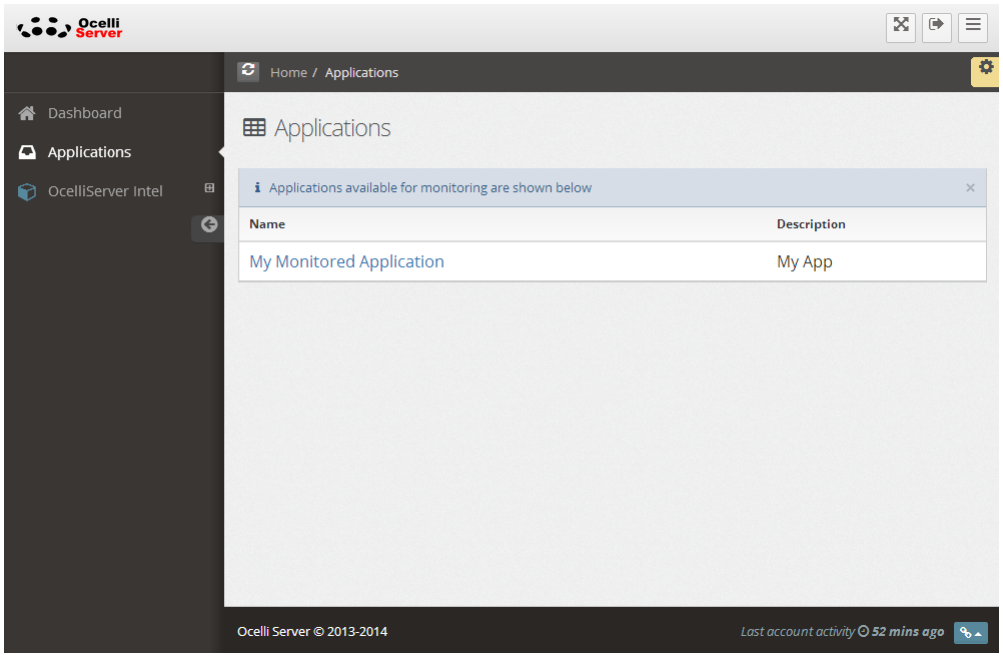
**Key Analysis Areas** There are certain metrics which will be recorded and monitored as each of the tests are run. The Ocelli Server itself (which is ingesting the data stream) will have its key metrics monitored, along with the nodes to which it is connected. Possible metrics to be monitored are listed below

- Average and Peak CPU Load on Ocelli Server
- Average and Peak CPU Usage of Ocelli Java Server Process
- Average and Peak CPU Usage of Elastic Search Server Process
- Average and Peak Memory Usage on Ocelli Server
- Average and Peak Memory Usage of Ocelli Java Server Process
- Average and Peak Memory Usage of Elastic Search Server Process
- Average and Peak Network Usage on Ocelli Server
- Average and Peak Disk Usage on Ocelli Server
- Average and Peak CPU Load on a Monitored Node
- Average and Peak Memory Usage on a Monitored Node
- Average and Peak Network Usage on a Monitored Node
- Average and Peak Disk Usage on a Monitored Node

These metrics will be used to determine the performance of Ocelli Server and extrapolate the possibility of scaling the system further.

### 5.3 Running the simulation

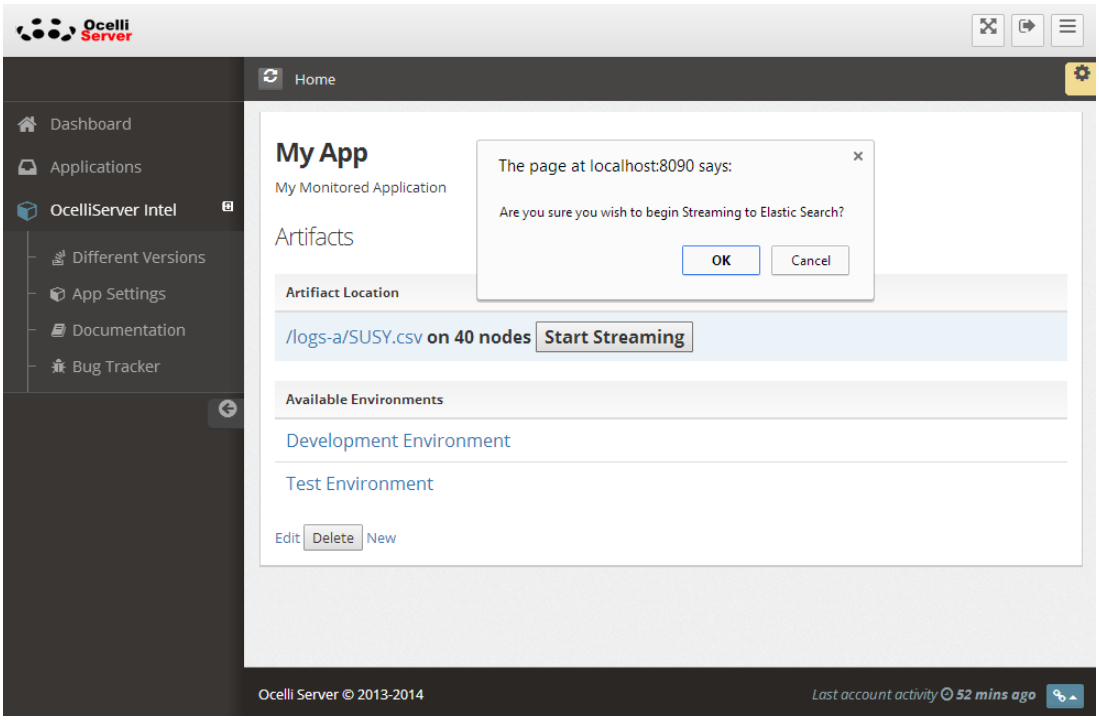
**Application Setup** The first step is to create the Application within the Ocelli Server UI, an example application is shown below




**Streaming Setup** Next, an Artifact must be selected for streaming to Elastic Search as show below, once the "Start Streaming" action has been confirmed in the Ocelli Server UI, data should begin streaming from the selected Artifact and appear in Elastic Search almost immediately. The Ocelli Server Java Application will connect via SSH to each of the servers one after another, so not all data will be streamed at once from each sever, rather it will gradualllly increase.

For all of the tests the following will hold true

- /var/log/access.log will be a single 1.6GB text file
- Elastic Search will be installed and running on a seperate server to Ocelli Server
- Each test will run for 5 minutes with a 5 minute warm up period occurring first




There is also serverside setup for the simulation in the configuration of the Ocelli SSH Server. The ocelli.yml configuration file is modified to activate simulation mode and to add two additional variables, tpsCheckInterval and simulationRunTimeMillis

```
#Check the transactions per second every x transactions
tpsCheckInterval: 1500

# Simulation mode
simulationMode: true

# Simulations run for 5 minutes by default
simulationRunTimeMillis: 300000
```

tpsCheckInterval checks the number of transactions per second that Ocelli is able to process downstream to the ElasticSearch server, whilst simulationRunTimeMillis stops Ocelli from streaming after a certain amount of time has passed. This allows for timeboxed tests to be performed very easily.

**Warm Up Phase** To warm up the JVM, the application is switched to "simulationMode: true" in ocelli.yml and the simulation is set to run for 5 minutes only. In the warm up phase Ocelli is also only connected connected to a single server on which it is streaming a single log from /var/log/access.log.

# 6 Results and Analysis

## 6.1 Warmup

During the warmup phase with Ocelli streaming from a single server the following results were observed in the application monitoring tool

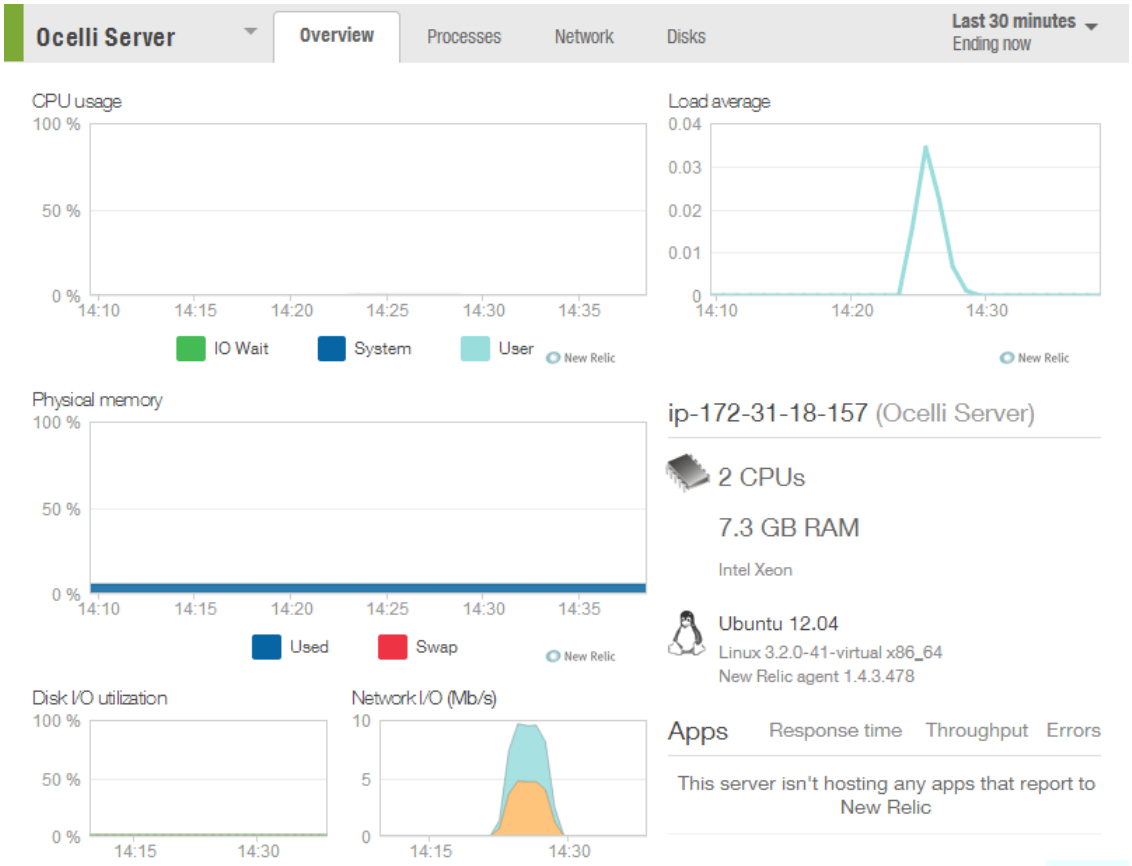



**Fig. 2.** Ocelli Warm Up Results

The most taxed resource on the Ocelli Server was network bandwidth which peaked at 10Mbps, all other resource usages were nominal. Ocelli Server peaked at 819 tps (compared with 769 pre-warmup) and ingested 237,528 transactions to elasticsearch over exactly 300 seconds.

| Attrubute | Value |
|---|---|
| Peak TPS | 819 |
| Average and Peak CPU Load on Ocelli Server | 0.5% / 6% |
| Average and Peak CPU Usage of Ocelli Java Server Process | 0.3% / 5.6% |
| Average and Peak CPU Usage of Elastic Search Server Process | 37.1%/46.7% |
| Average and Peak Memory Usage on Ocelli Server | 400 MB / 426 MB |
| Average and Peak Memory Usage of Ocelli Java Server Process | 200 MB / 210 MB |
| Average and Peak Memory Usage of Elastic Search Server Process | 200 MB / 380 MB |
| Average and Peak Network Usage on Ocelli Server | 10 Mbps |
| Peak Disk Usage on Ocelli Server | 2 IOPS (0.1%) |
| Average and Peak CPU Load on a Monitored Node | 1% |
| Average and Peak Memory Usage on a Monitored Node | 50MB / 55MB |
| Average and Peak Network Usage on a Monitored Node | 2 Mbps / 5 Mbps |
| Average and Peak Disk Usage on a Monitored Node | 1% |

### 6.2 Test 1 - 10 Servers

During the next phase with Ocelli streaming from 10 app server instances the following results were observed in the application monitoring tool

The most taxed resource on the Ocelli Server was again, network bandwidth, which peaked at 65Mbps, all other resource usages were nomina except for CPU which started to rise to an average of 25%. Ocelli Server peaked at 5084 tps (compared with 769 pre-warmup) and ingested 1,522,352 transactions to elasticsearch over exactly 300 seconds. At this point we can see that there are some key metrics that are starting to max out.

- CPU Usage of Elastic Search is now at 80.7% Peak
- Network Bandwidth for Ocelli Server is at 35 Mb/s Peak

| Attrubute | Value |
|---|---|
| Peak TPS | 5084 |
| Average and Peak CPU Load on Ocelli Server | 25% / 50% |
| Average and Peak CPU Usage of Ocelli Java Server Process | 20% / 44.6% |
| Average and Peak CPU Usage of Elastic Search Server Process | 37.1%/80.7% |
| Average and Peak Memory Usage on Ocelli Server | 410 MB / 416 MB |
| Average and Peak Memory Usage of Ocelli Java Server Process | 244 MB / 250 MB |
| Average and Peak Memory Usage of Elastic Search Server Process | 350 MB / 390 MB |
| Average and Peak Network Usage on Ocelli Server | 35 Mb/s |
| Average and Peak Network Usage on Elastic Search Server | 25 Mb/s |
| Peak Disk Usage on Ocelli Server | 2 IOPS (0.1%) |
| Peak Disk Usage on Elastic Search Server | 80 IOPS (4.6%) |
| Average and Peak CPU Load on a Monitored Node | 1% |
| Average and Peak Memory Usage on a Monitored Node | 50MB / 55MB |
| Average and Peak Network Usage on a Monitored Node | 2 Mbps / 5 Mbps |
| Average and Peak Disk Usage on a Monitored Node | 1% |

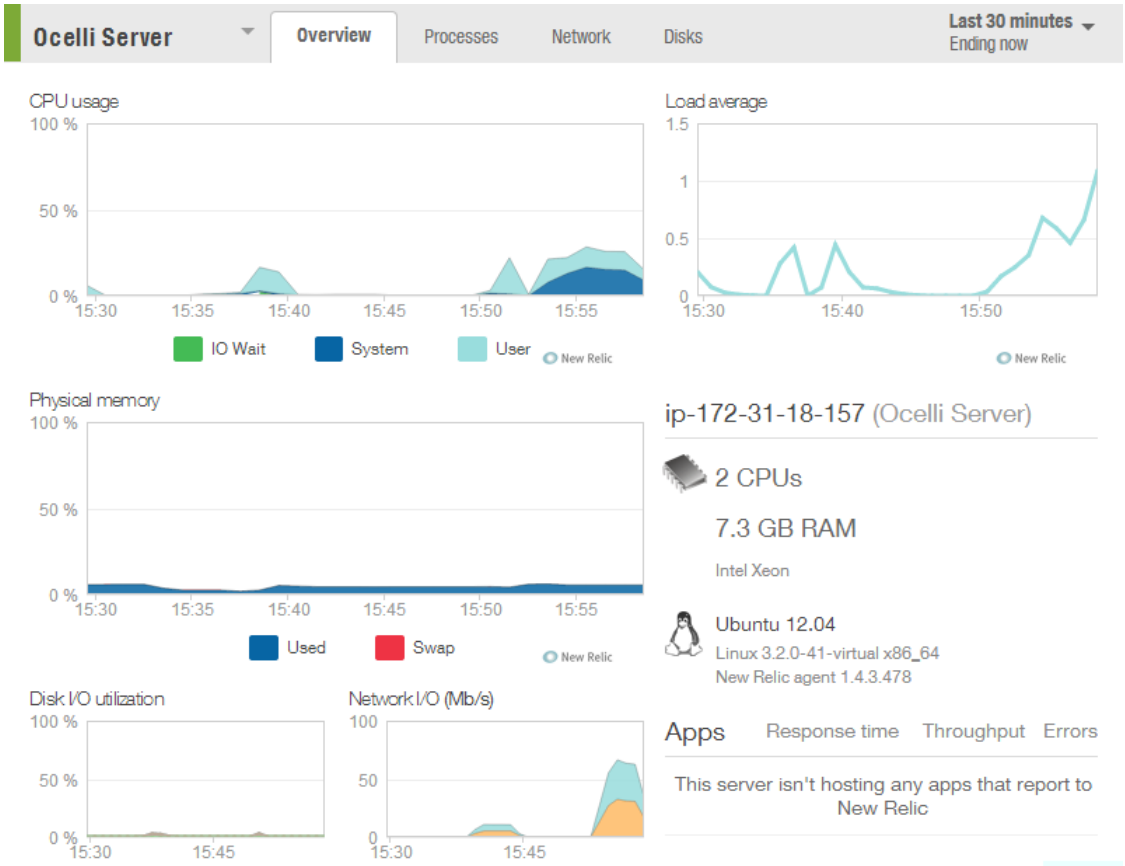



**Fig. 3.** Ocelli Test 1 (10 Servers) - Results

One additional point of note was a slight delay in pickup from one of the SSH servers, which was roughly 10,000 transactions behind the rest of the streams. Once it was streaming, it kept up with the rest of the servers.

### 6.3 Test 2 - 20 Servers and 98 Servers

During the test at 20 servers it appears that we have reached the limit of the chosen instance trypes, from both a networking and CPU perspective. From the chart below we can see that we were unable to obtain any more bandwidth from Amazon between the first and second tests. Ocelli Server peaked at 5564 tps and ingested 1,635,360 transactions to elasticsearch over exactly 300 seconds

However, we were still bale to obtain a slight increase in peak TPS @ 5564 showing that doubling the amount of attached nodes still allows for an ingest rate of 278 transactions per server. This may still be enough to debug issues in real time during a crisis event. The slight increase can be attributed to further

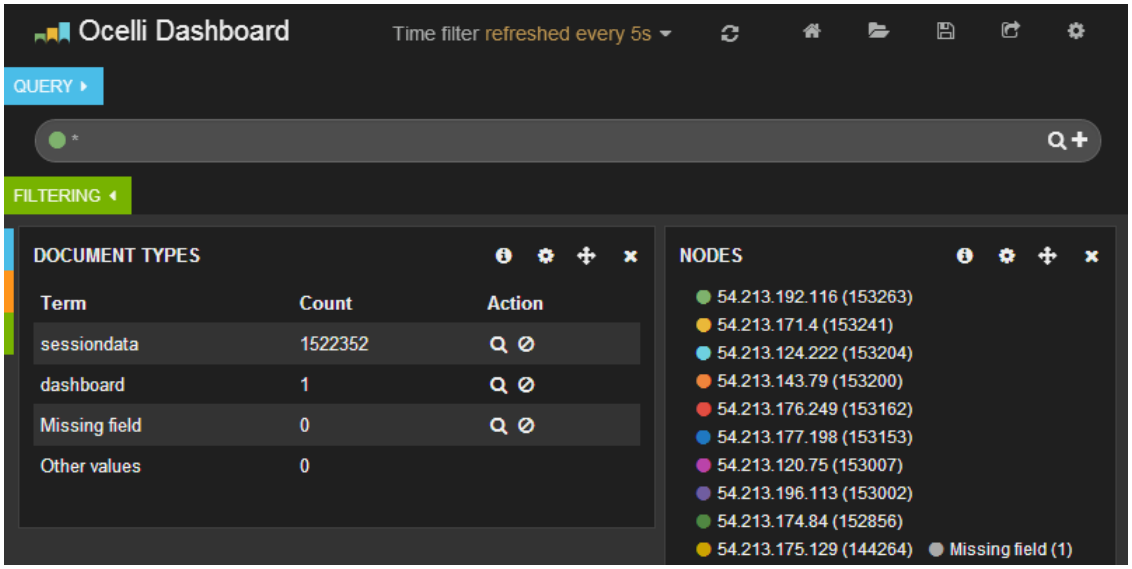



**Fig. 4.** Ocelli Test 1 (Kibana dashboard showing server 53.213.175.129 fell behind)

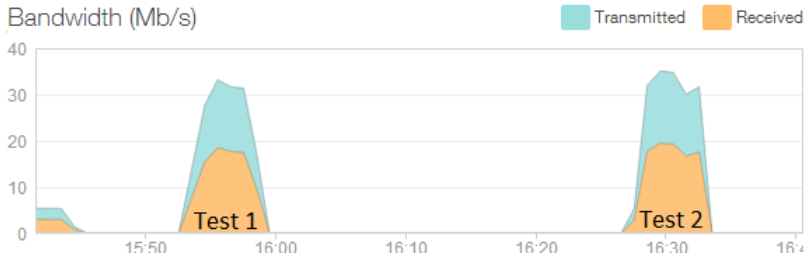



**Fig. 5.** Comparison of network bandwidth for Ocelli Server between Test 1 and Test 2

work performed by Elastic Search server which was not completely topped out on bandwith, allowing it to write additional transactions to disk, the increase in IOPS for Elastic Search shows it was still forced to make more writes in this test.

| Attrubute | Value |
|---|---|
| Peak TPS | 5564 |
| Average and Peak CPU Load on Ocelli Server | 40% / 50% |
| Average and Peak CPU Usage of Ocelli Java Server Process | 30% / 48.6% |
| Average and Peak CPU Usage of Elastic Search Server Process | 80.1%/92.2% |
| Average and Peak Memory Usage on Ocelli Server | 410 MB / 416 MB |
| Average and Peak Memory Usage of Ocelli Java Server Process | 300 MB / 300 MB |
| Average and Peak Memory Usage of Elastic Search Server Process | 410 MB / 410 MB |
| Average and Peak Network Usage on Ocelli Server | 35 Mb/s |
| Average and Peak Network Usage on Elastic Search Server | 26 Mb/s |
| Peak Disk Usage on Ocelli Server | 2 IOPS (0.1%) |
| Peak Disk Usage on Elastic Search Server | 114 IOPS (4.6%) |
| Average and Peak CPU Load on a Monitored Node | 1% |
| Average and Peak Memory Usage on a Monitored Node | 50MB / 55MB |
| Average and Peak Network Usage on a Monitored Node | 2 Mbps / 5 Mbps |
| Average and Peak Disk Usage on a Monitored Node | 1% |

Before upgrading the Ocelli and Elastic Search servers, a test was performed at 98 nodes with the same configuration, Ocelli Server peaked at 5836 tps and ingested 1,750,863 transactions to elasticsearch over exactly 300 seconds. This is a 4% performance improvement. One interesting result from this test was that although we did not manage to increase the throughput, the distribution of data collected per server was extremely even, to within +- 1%. This means that there was no lag in connecting to the servers or collecting the data in the 98 node test, indicating that the outlier in Test 1 may have been just an anomaly. This can be seen below

However, we can see that we have completely exhausted the resources on the Elastic Search server and it cannot keep up with the data ingest.

| Attrubute | Value |
|---|---|
| Peak TPS | 5564 |
| Average and Peak CPU Load on Ocelli Server | 40% / 60% |
| Average and Peak CPU Usage of Ocelli Java Server Process | 39% / 52.6% |
| Average and Peak CPU Usage of Elastic Search Server Process | 80.1%/92.2% |
| Average and Peak Memory Usage on Ocelli Server | 1000 MB / 1050 MB |
| Average and Peak Memory Usage of Ocelli Java Server Process | 855 MB / 860 MB |
| Average and Peak Memory Usage of Elastic Search Server Process | 500 MB / 517 MB |
| Average and Peak Network Usage on Ocelli Server | 40 Mb/s |
| Average and Peak Network Usage on Elastic Search Server | 30 Mb/s |
| Peak Disk Usage on Ocelli Server | 2 IOPS (0.1%) |
| Peak Disk Usage on Elastic Search Server | 107 IOPS (4.4%) |
| Average and Peak CPU Load on a Monitored Node | 1% |
| Average and Peak Memory Usage on a Monitored Node | 50MB / 55MB |
| Average and Peak Network Usage on a Monitored Node | 2 Mbps / 5 Mbps |
| Average and Peak Disk Usage on a Monitored Node | 1% |

At 100 nodes, we are at capacity with the following resources

Ocelli Server Network Bandwidth - 100% (40 Mb/s) Elastic Search Server Network Bandwidth - 80% (30 Mb/s) Elastic Search Server CPU - 100%

For the next test we will upgrade the Elastic Search Server so that it has more CPU and more network bandwidth.

### 6.4 Test 3 - 100 Servers, Upgraded Elastic Search

For this test, the Elastic Search Server is upgraded to a M3 General Purpose Double Extra Large (m3.2xlarge)

| Attrubute | Value |
|---|---|
| Max Network Bandwidth | 100 Mb/s |
| CPU's | 8 Core (26 ECU) |
| Memory | 30 GB |

The results of this test are surprising, by upgrading the Elastic Search Server, we actually unlock a 2x increase in scale without upgrading the Ocelli Server. In fact, it seems that the Elastic Search server has been holding the Ocelli Server back. Ocelli Server peaked at 13163 tps and ingested 3,948,915 transactions to elasticsearch over exactly 300 seconds. This is a 136% performance improvment from Test 2 at 98 nodes.

There are some interesting observations to made from this test.

Firtstly, even though the rated network throughput on the Ocelli Server is still 40 Mb/s, it manages to increase its through put for combined send and recieve to 83.5 MB/s. It is possible that this is due to the fact that it is now on an ingress network link of 100 Mb/s to the Elastic Search server, which is now at 100 MB/s and as such, can take advantage of that bandwith by the nature of

being connected to that server. However, the addition of this bandwidth means that Ocelli Server is now using more CPU to push the data, and as such is beginning to also max out on CPU. For the next test, we will upgrade the Ocelli Server to an m3.2xlarge also. The Elastic search server itself is using about 40% CPU on its new configuration.

| Attrubute | Value |
|---|---|
| Peak TPS | 5564 |
| Average and Peak CPU Load on Ocelli Server | 90% / 90% |
| Average and Peak CPU Usage of Ocelli Java Server Process | 92.0% / 93.2% |
| Average and Peak CPU Usage of Elastic Search Server Process | 40.1%/40.7% |
| Average and Peak Memory Usage on Ocelli Server | 1010 MB / 1020 MB |
| Average and Peak Memory Usage of Ocelli Java Server Process | 855 MB / 870 MB |
| Average and Peak Memory Usage of Elastic Search Server Process | 400 MB / 410 MB |
| Average and Peak Network Usage on Ocelli Server | 83.5 Mb/s |
| Average and Peak Network Usage on Elastic Search Server | 62 Mb/s |
| Peak Disk Usage on Ocelli Server | 2 IOPS (0.1%) |
| Peak Disk Usage on Elastic Search Server | 145 IOPS (4.4%) |
| Average and Peak CPU Load on a Monitored Node | 1% |
| Average and Peak Memory Usage on a Monitored Node | 50MB / 55MB |
| Average and Peak Network Usage on a Monitored Node | 2 Mbps / 5 Mbps |
| Average and Peak Disk Usage on a Monitored Node | 1% |

### 6.5 Test 4 - 98 Servers, Upgraded Ocelli Server

For this test, the Elastic Search Server is upgraded to a M3 General Purpose Double Extra Large (m3.2xlarge)

During this test it is observed that although we have increased our throughput, Elastic Search has yet again become the bottle neck. Ocelli Server peaked at 22976 tps and ingested 6,893,024 transactions to elasticsearch over exactly 300 seconds. The Ocelli server read data at 144 Mb/s and sent to Elastic Search at 150 Mb/s, however Elastic search only reported ingesting at 74 Mb/s, with a combined network throughput of aroun 100 Mb/s as show below.

## 7 Summary and Conclusions

## 8 Nomenclature

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\begin{thebibliography}{}  % (do not forget {})
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\bibitem[1982]{clar:eke}
Clarke, F., Ekeland, I.:
Nonlinear oscillations and boundary-value problems for
Hamiltonian systems.
Arch. Rat. Mech. Anal. 78, 315--333 (1982)
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\end{thebibliography}
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*Sample Output*

## References

Clarke, F., Ekeland, I.: Nonlinear oscillations and boundary-value problems for Hamiltonian systems. Arch. Rat. Mech. Anal. 78, 315–333 (1982)

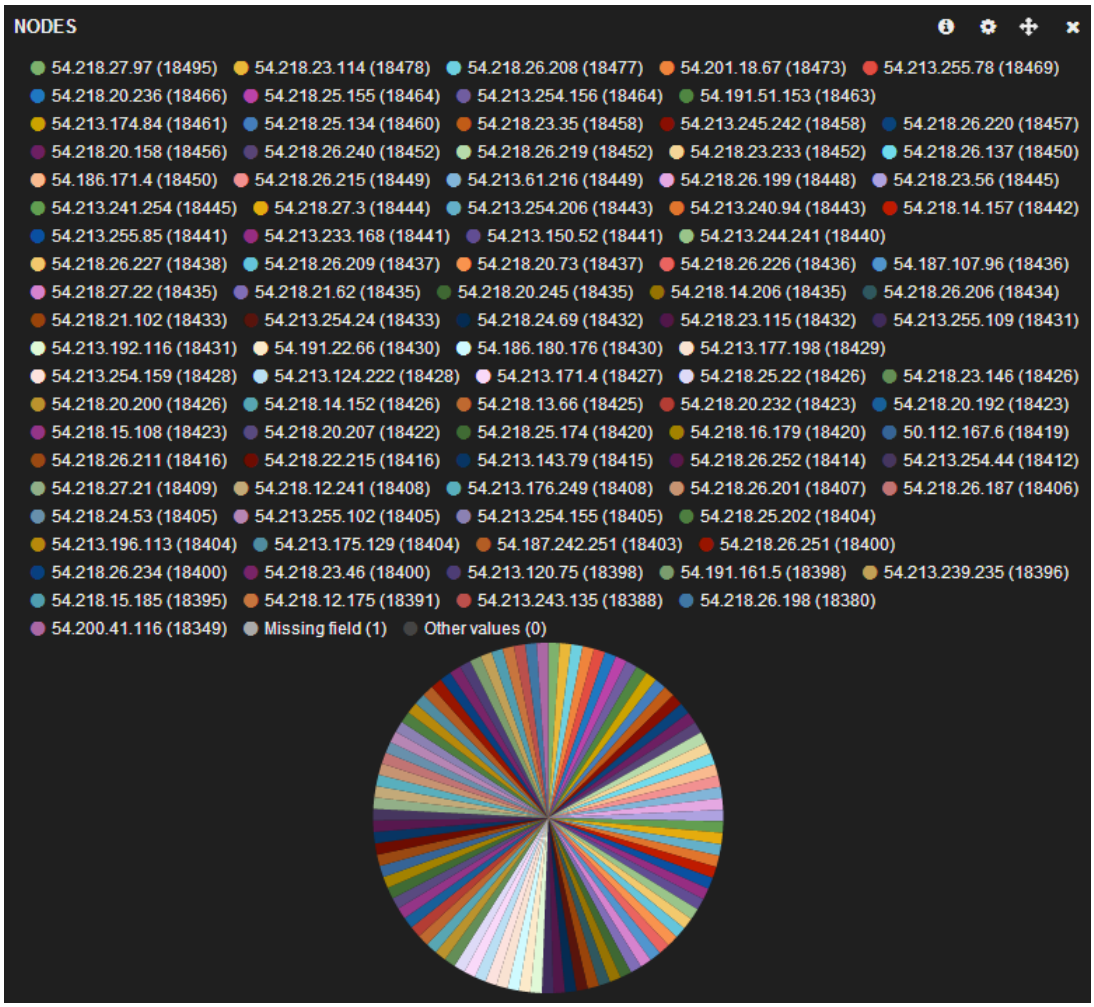


**Fig. 6.** Kibana showing even distribution of data collected across nodes ( 18.4k transactions per node)

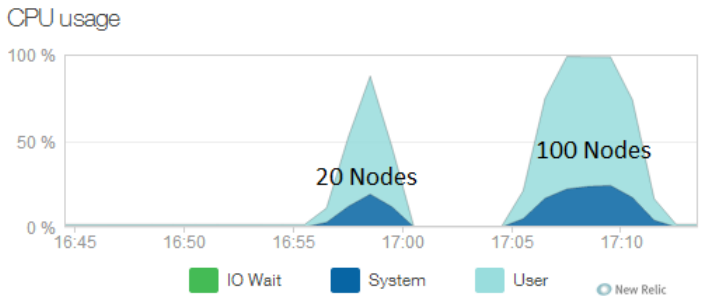


**Fig. 7.** Elastic Search Server CPU ingesting data from 20 and 100 nodes respectively

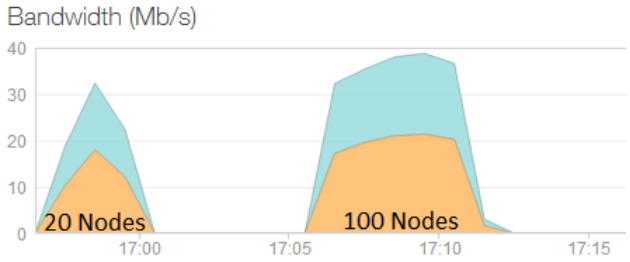


**Fig. 8.** Network bandwidth usage at 20 and 100 nodes respectively for Ocelli Server

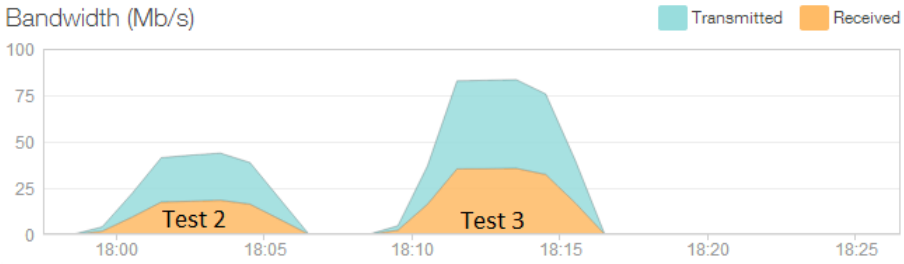


**Fig. 9.** Network between test 2 and test 3 showing increased bandwidth availability for Ocelli Server

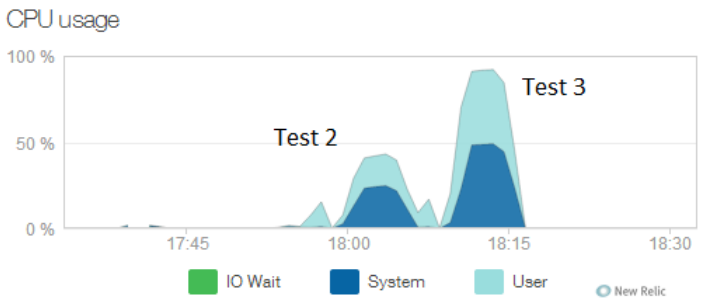


**Fig. 10.** Ocelli Server nearing 100% CPU utilization at 100 nodes for test 3

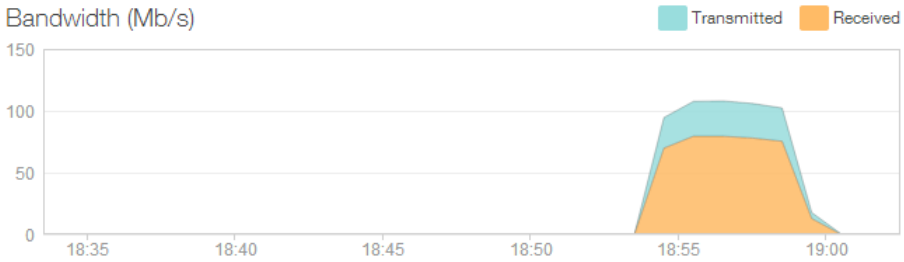


**Fig. 11.** Elastic Search network bandwith chart showing 74 Mb/s ingress with 28.2 Mb/s transmitted