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iForesight: Intelligent Cloud Operations and Maintenance

iForesight relies on artificial intelligence, event correlation, and time-based technologies to effectively detect and predict anomalous behaviors during cloud operations to reduce the workload of human operators

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German Research Center
Munich, Germany

CERN openlab OpenDay
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Geneva

Executive Summary

Goal. Develop the next generation of DevOps tools & services for monitoring and operational automation. Drive **artificial intelligence** into **autonomous cloud operations**

Background. Cloud providers are increasingly interested in exploiting the use of machine learning to build new tools for autonomous cloud operations (Azure Insights, Amazon AWS, Google, HP Operations Bridge, Salesforce NoOps)

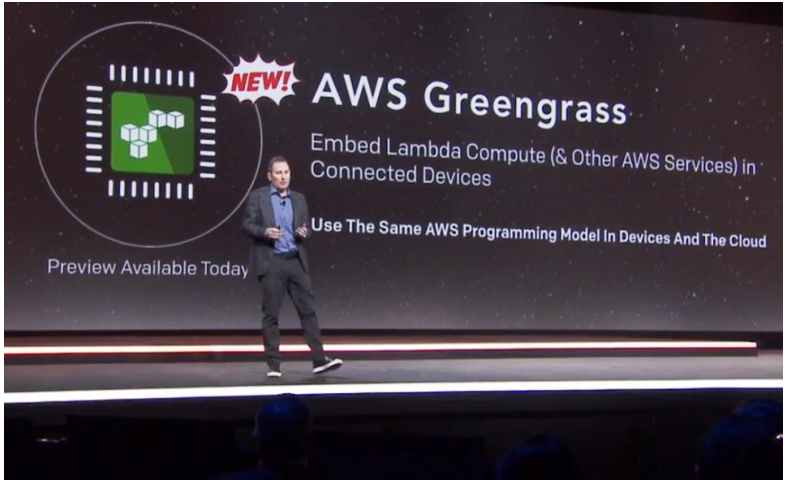
Objectives. Provide advanced solutions for autonomous cloud operations for Open Telekom Cloud (OTC), Fusion Cloud Stack (FCS) and FusionSphere

Technologies. **Machine Learning**, **data mining**, **time-series analysis**, and **distributed tracing technologies**

Edge Computing

Amazon AWS

- Amazon is interested in local, mini data-centres for its huge cloud business.
- It may be able to disrupt other telecoms/IT businesses, and steer some “edge computing” technology standards and paths
- AWS Greengrass powers local edge gateways and appliances. It works as an extension to AWS IoT.



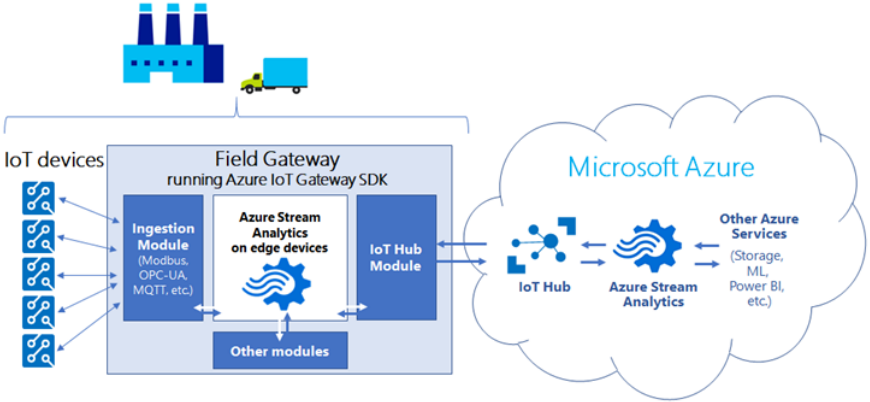
AWS Greengrass has a small footprint that can run on system-on-a-chip devices like Raspberry Pi and BeagleBone powered by ARM processors

Benefits

- Reduced latency between the devices and data processing layer
- Reduced bandwidth costs involved in ingesting large amount of data to the cloud
- Compliance and security by retaining the sensitive data locally

Microsoft IoT Edge

- Run artificial intelligence at the edge
- Perform edge analytics
- Deploy IoT solutions from cloud to edge
- Manage devices centrally from the cloud
- Operate with offline and intermittent connectivity



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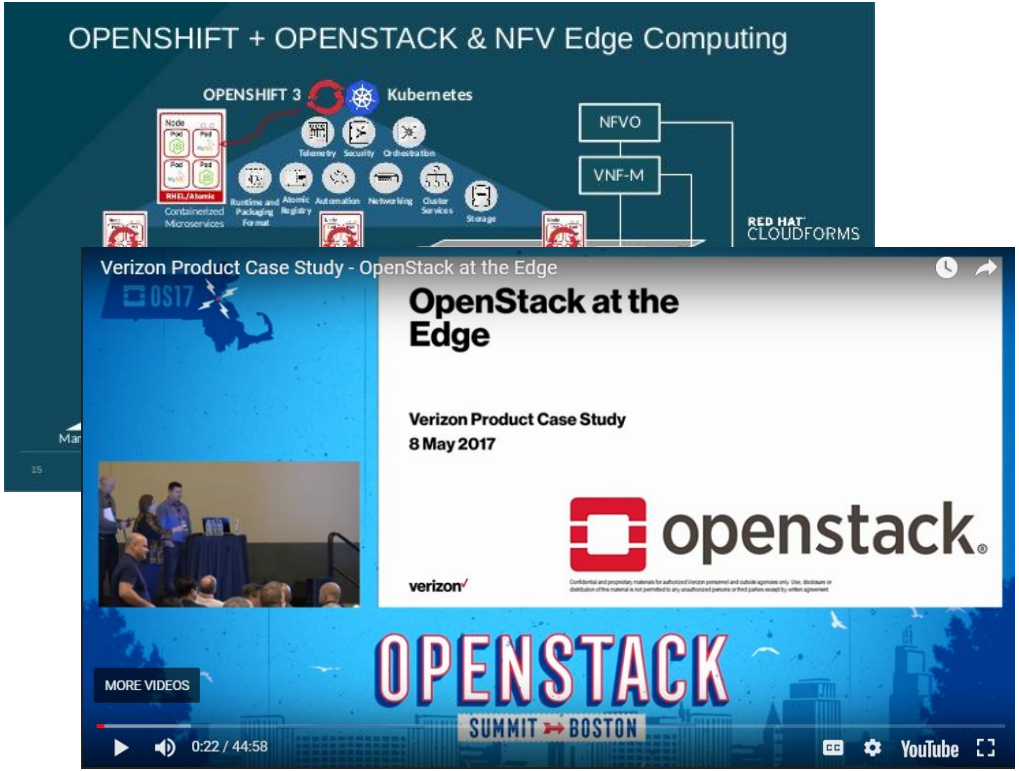
OpenStack and Edge Computing



Verizon's cloud-in-a-box offering based on OpenStack delivers computing to the edges
Boston Summit 2017

Complex Systems and Reliability

Companies

- Microsoft's
  - Data centers average failure rate is 5.2 devices/day and 40.8 links/day
  - Median time to repair of ca. 5 minutes and a maximum of 1 week.
- Google
  - New cluster over one year
  - 5 times rack issues 40-80 machines seeing 50 percent packet loss
  - 8 network maintenance events (four of which might cause ~30-minute random connectivity losses).
  - 3 router failures resulting in the need to pull traffic immediately for an hour
- CENIC
  - 500 isolating network partitions with median 2.7 and 32 minutes
  - 95th percentile of 19.9 minutes and 3.7 days, respectively for software and hardware problems

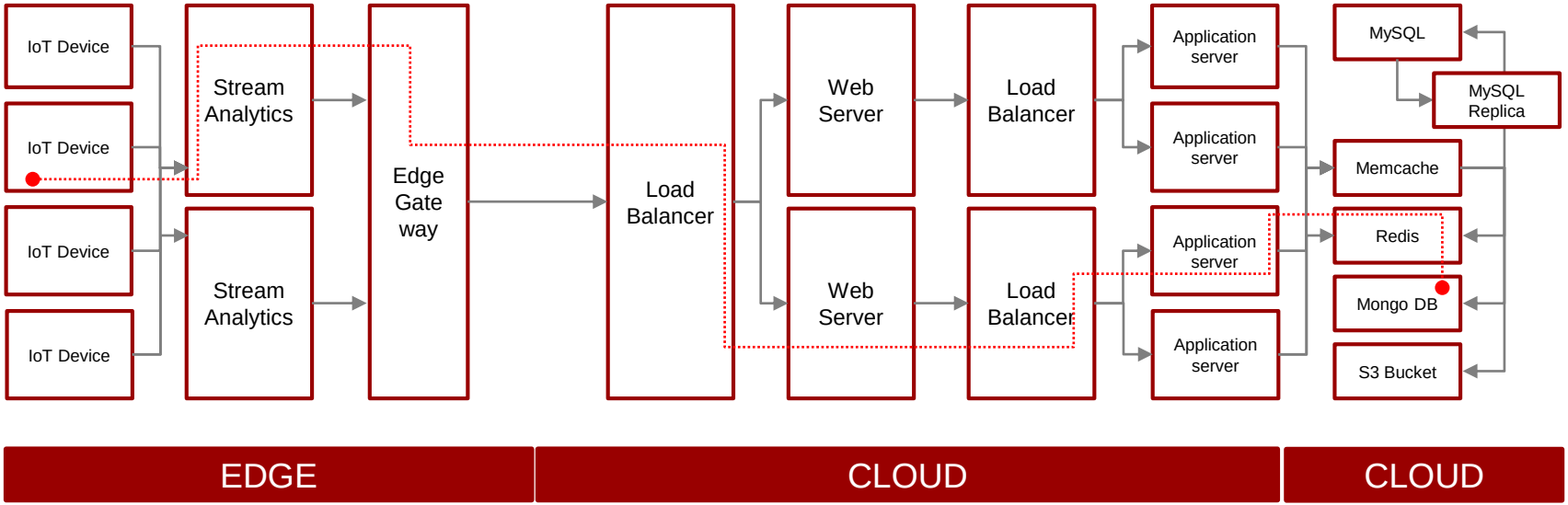
Applications

- MongoDB
  - Separated primary from its 2 secondaries
  - 2 hours later the old primary rejoined and rolled back everything on the new primary
- Redis
  - A network partition isolated the Redis primary from all secondaries.
  - Every API call caused the billing system to recharge customer credit cards automatically, resulting in 1.1 percent of customers being overbilled over a period of 40 minutes.
- MySQL
  - The partition caused inconsistency in the MySQL database.
  - Because foreign key relationships were not consistent, Github showed private repositories to the wrong users' dashboards and incorrectly routed some newly created repositories.
- Elasticsearch
  - For several seconds, Elasticsearch is happy to believe two nodes in the same cluster are both primaries, will accept writes on both of those nodes, and later discard the writes to one side.

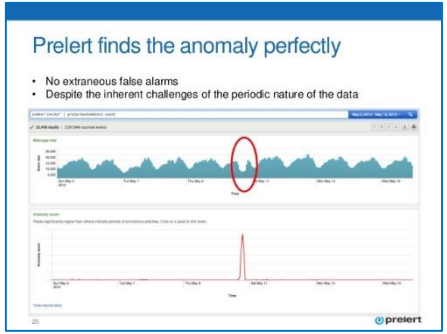
https://queue.acm.org/detail.cfm?id=2655736
Peter Bailis, UC Berkeley
Kyle Kingsbury, Jepsen Networks

Troubleshooting Multi-clouds

A service request failed
Which path was followed?

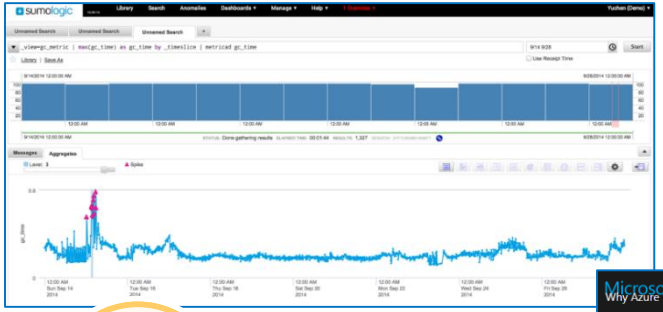


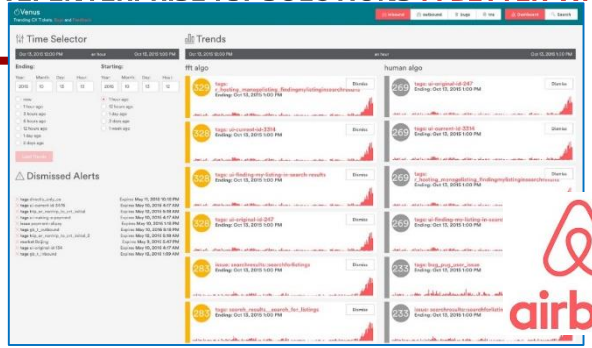
Anomaly Detection Services



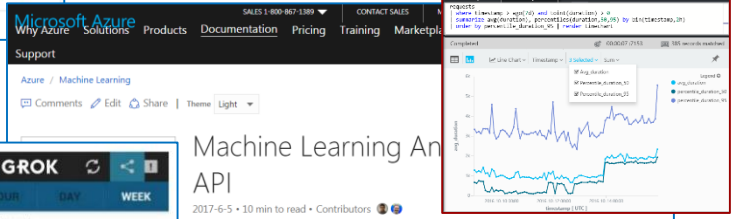
http://www.prelert.com/docs/splunk_app/latest/

https://www.sumologic.com/resource/datasheet/anomaly-detection/





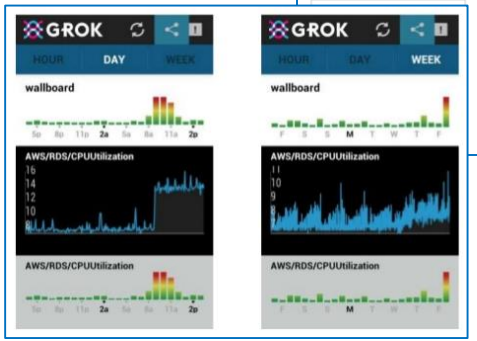
https://medium.com/airbnb-engineering/how-airbnb-manages-to-monitor-customer-issues-at-scale-b883301ca461



Microsoft Insights

https://docs.microsoft.com/en-us/azure/machine-learning/machine-learning-apps-anomaly-detection-api

Generic Analysis	Butterfly iForesight	IoT Analytics	Custom Solutions
• Decision trees • SVN • For experts • Too difficult	• Flexible • Explore and Fix • AIOps as Code	• Specific Analysis • Uses Forms • Predefined Domains	• Too expensive • Too specific



https://grokstream.com/

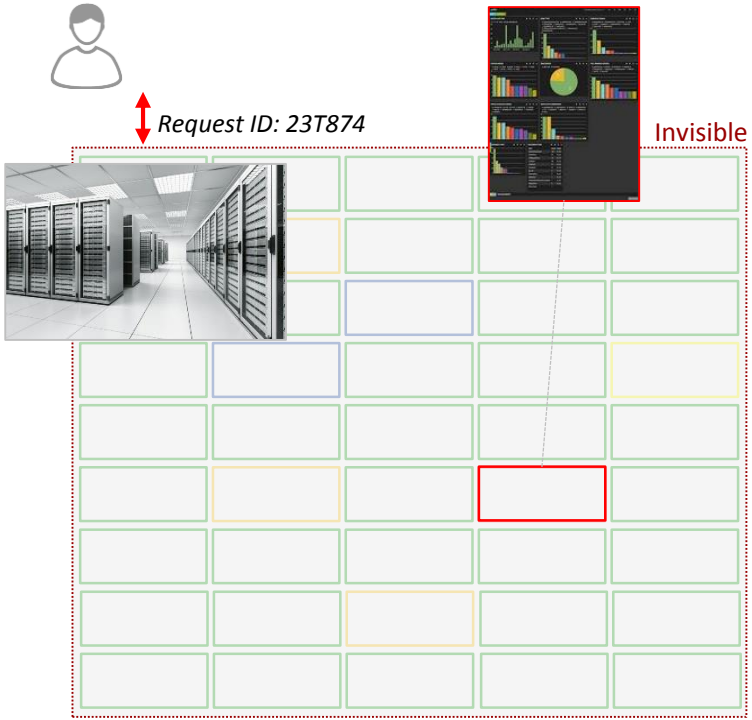
Twitter S-H-ESD Algorithm

- https://github.com/nlittlepoole/thermometr

Prelert:	1st class citizen: Log lines (text patterns) + AI
SumoLogic:	1st class citizen: Log lines (text patterns) + AI
Grok:	1st class citizen: Sys. Metrics (text patterns) + AI
Twitter:	1st class citizen: Log lines (text patterns) + AI
AirBnB:	1st class citizen: JSON (isolated time-series) + AI
Azure:	1st class citizen: JSON (isolated time-series) + AI
iForesight:	1st class citizen: **Distributed Traces + AI**

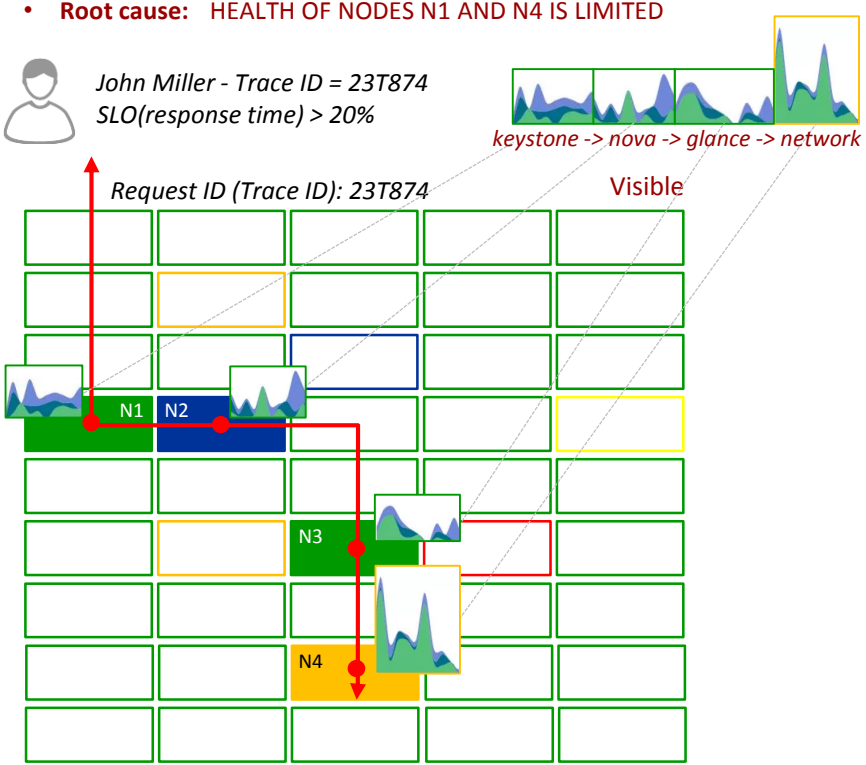
Log/Metrics vs. Distributed Traces Monitoring

- **SLA/SLO**: OTC replies within 0.5 seconds of receiving a request
- **Scenario:** The request for the execution of a service was 50% slower when compared to 12h ago.
- **Root cause:** NOT KNOWN



Log/Metrics Monitoring

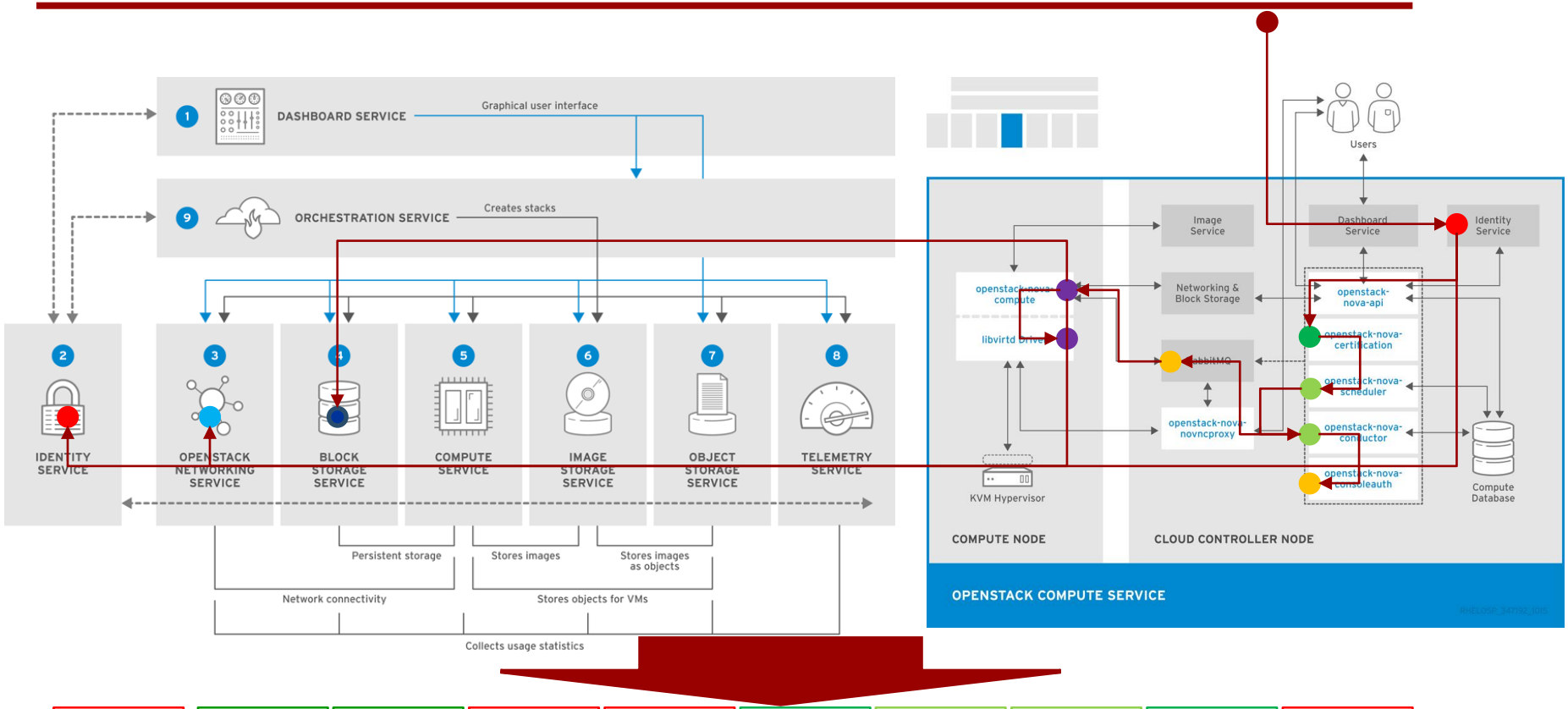
- **SLA/SLO**: OTC replies within 0.5 seconds of receiving a request
- **Scenario:** The request for the execution of a service was 50% slower when compared to 12h ago.
- **Root cause:** HEALTH OF NODES N1 AND N4 IS LIMITED



Distributed Tracing Monitoring

SEVERE
HIGH
ELEVATED
GUARDED
NORMAL

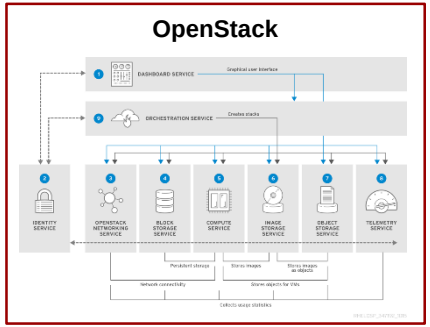
Distributed Tracing in OpenStack



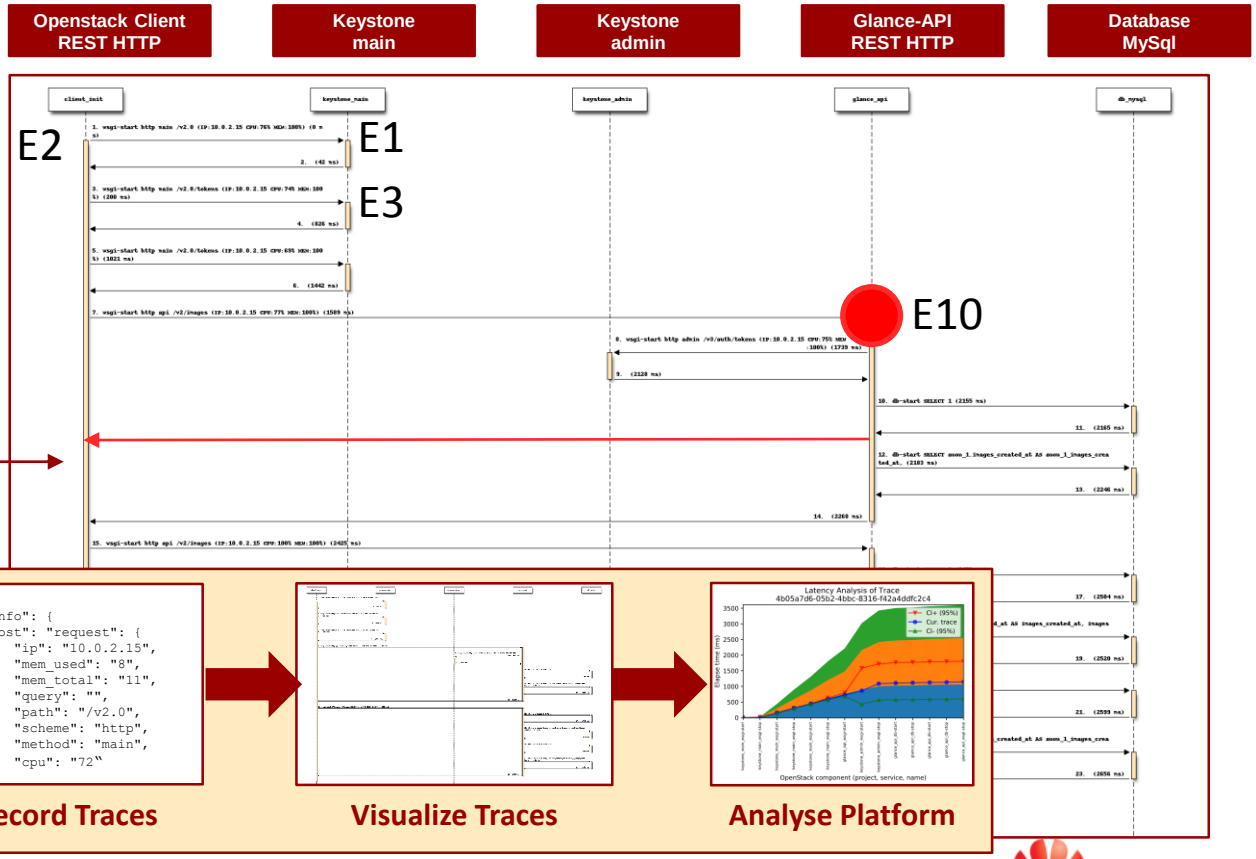
A	B	B	A	C	D	E	E	D	C
(18, 17, 17)	(23, 18, 17)	(23, 18, 17)	(18, 17, 17)	(14, 17, 17)	(26, 14, 17)	(34, 26, 17)	(34, 26, 17)	(26, 14, 17)	(18, 17, 17)

https://access.redhat.com/documentation/en/red-hat-openstack-platform/8/paged/architecture-guide/chapter-1-components

Distributed Tracing



Tracing Infrastructure




```
service_tracing(ctx)
process_tracing(ctx)
progress_task_tracing
horizontal_process
end_tracing(ctx)
hold_tracing(ctx)
start_tracing(ctx)
```

Trace Requests


```
{
    "info": {
    "host": "request": {
        "ip": "10.0.2.15",
        "mem_used": "8",
        "mem_total": "11",
        "query": "",
        "path": "/v2.0",
        "scheme": "http",
        "method": "main",
        "cpu": "72"
```


Record Traces

Visualize Traces

Analyse Platform

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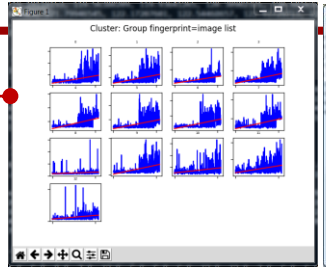
Advanced Trace Analysis

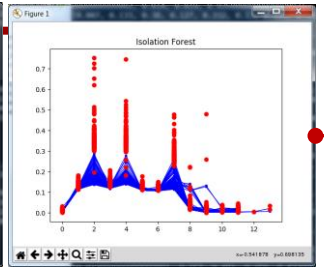
1. Trend Analysis
- *Script*: *detect_trend_transitions.py*
- How does the performance of FusionSphere subsystems change over time?

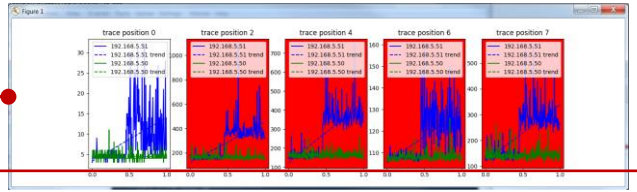
2. Controller Efficiency Comparison
- *Script*: *controller_anomalies.py*
- Identify FS controller nodes with poor performance

3. Outlier Detection for SLO
- *Script*: *detect_outliers.py*
- Identify traces with abnormal performance characteristics

4. Root Cause Analysis
- *Script*: *trace_troubleshooting.py*
- Which FS components are responsible for poor performance?





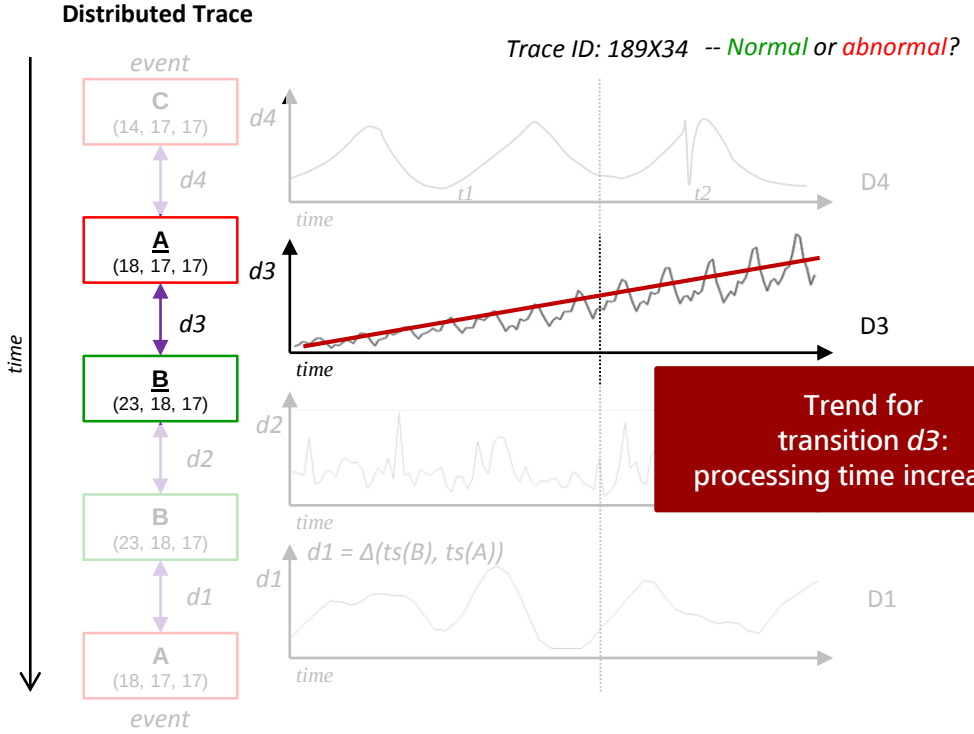



```
iForesight service
------------------
Start trace and transition analysis usinglinear regression? [Y/n] y
Select the time window (in days) to analyze: 2
Anomalous traces received with a trend degree>15 over thelast 2 days
  TID: 7674b8b6340ade05a83c0d856f832149, Tenant-ID: 97130401-e102-4676-b8a9-f47b149ba577
  TID: a6cf891e548cb6debe049f4f55af9167, Tenant-ID: 9c436f88-8eef-449d-99cf-dcad1b58145e
getting transitions from anomalous traces
3  28 transitions received
Select the threshold for labelinganomalies (0-90): 0
Anomalous transition: image_3d7079e
Anomalous transition: image_b337fa9
Anomalous transition: image_2711e78
Anomalous transition: image_551dacd
Anomalous transition: image_5445add
Anomalous transition: image_3344090
Anomalous transition: image_f85ab8c
Anomalous transition: image_5f147fa
Anomalous transition: image_81774ed
Anomalous transition: image_03bf6c2
Anomalous transition: image_35d88b4
Getting resources associated with transitions
  2 resources to consider: glance, keystone
Root cause of anomalies.
  Resource: keystone (support: 17)
  Resource: glance (support: 5)
```

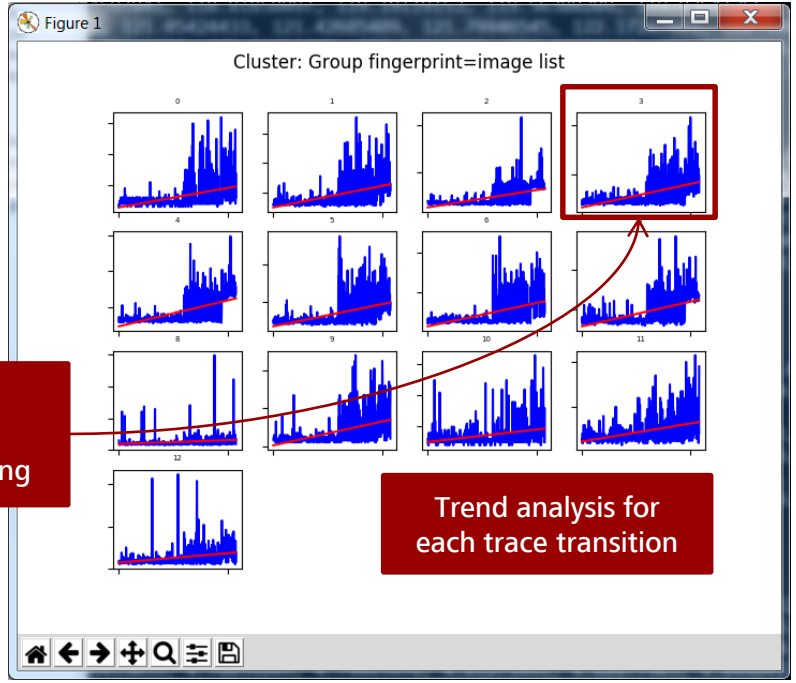
AI Algorithms	Status
Trend Analysis	OK (-)
Outlier Detection	OK (-)
Root Cause Analysis	OK (-)
Spikes & Dips	TBD

AI Algorithms	Status
Mean Shift	TBD
Ramp up	TBD
Distribution change	TBD
Deep Learning	TBD

Advanced Trace Analysis



Trend for transition *d3*: processing time increasing



Trend analysis for each trace transition

Advanced Trace Analysis

Identify FusionSphere controller nodes with poor performance

Workload analysis

Time Window (windows)
- *time interval of traces to consider*

Cluster (transition, start-end)
- *place similar traces together into clusters*

Aggregate (project, service, path, query, sql, rpc)
- *aggregates trace events to analyze*

Group by (host, ip)
- *Group aggregates based on some property*
- *group_by(left.ip)*

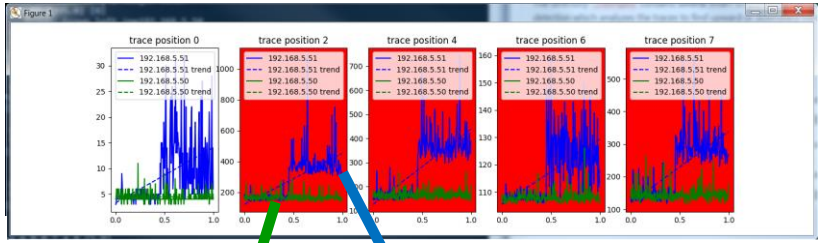
Execute Machine Learning algorithm
- *ML_TSA_method(…)*

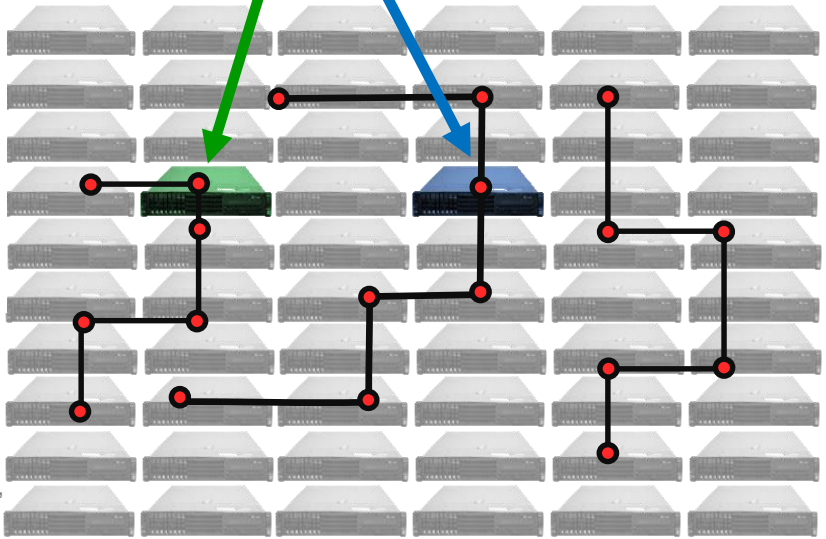
Retrieve Results
- *get_results(…)*

***Smart Script*: controller_anomalies.py**
iForesight SDK

```
# Windowing: set a temporal window to analyze traces
i4sight.window(when.past(weeks=8), when.past(weeks=1),
               wtype='train')

# Clusters traces with the same structure
i4sight.cluster(itype='structure', similarity=1.0)

# Aggregate the events of traces into smaller structures
i4sight.aggregate(itype='transition')

# Group transitions by IP Address
i4sight.group_by(['left.ip'])

# Execute linear regression to each group
i4sight.regression()

result = i4sight.get_result()
```

FS controller latency **for each transition** detected increased processing latency of **blue controller**





FusionSphere, FCS, OTC

Controller Nodes

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Advanced Trace Analysis

Isolation Forest

- **Unsupervised** machine learning algorithm, does not require labeled data for training.

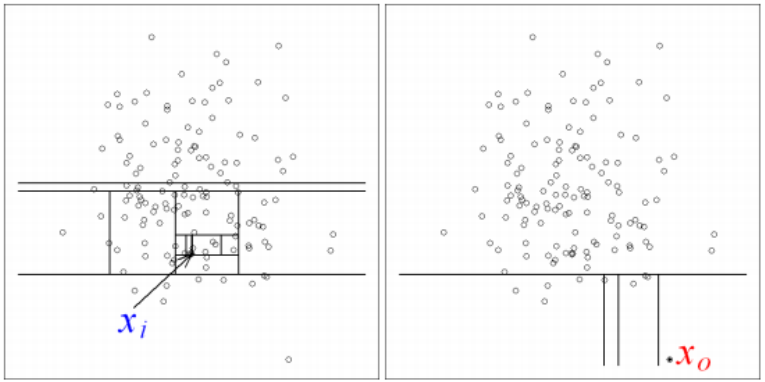
Algorithm

The algorithm 'isolates' traces by randomly selecting a transition and then randomly selecting a split value for its elapsed time between the maximum and minimum values.

1. Recursive (and random) partition of data represented as a tree
2. The end of the tree is reached once the recursive partition of elements is finished. The distance taken to reach the outlier is far less than that for the normal elements.
3. The distance of the tree path is averaged and normalized to calculate a anomaly score.
   - A score=1 is labeled as an outlier.
   - Values close to 0 are considered normal.

Parameters

- *Feature vectors*. Elapsed time of each trace transition
- *Contamination*. Estimated fraction of outliers in the training data set.



(a) Isolating x_i (b) Isolating x_o

Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. 2012. Isolation-Based Anomaly Detection. ACM Trans. Knowl. Discov. Data 6, 1, Article 3 (March 2012), 39 pages. DOI=http://dx.doi.org/10.1145/2133360.2133363

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