Anomaly Detection in CI Jobs https://etherpad.openstack.org/p/wadci

tdecacqu@redhat.com

2018-03-08





Anomaly Detection in CI Jobs

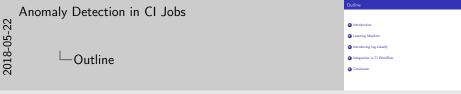
tdecacqu@redhat.com 2018-03-08





Outline

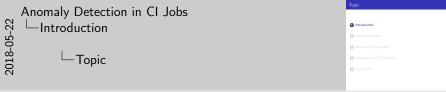
- Introduction
- 2 Learning Machine
- 3 Introducing log-classify
- 4 Integration in CI Workflow
- Conclusion



- Slides and materials are available at https://github.com/TristanCacqueray/opendevconf Please clone and execute the start.sh script now to cache the dataset.
- The goal of this workshop is to present a new anomaly extraction workflow for CI job results.
- We will see how machine learning methods can be used to compare job results and detect anomalies.
- Then, we will learn how to use the log-classify tool.
- Lastly, we will see how this workflow can be integrated with CI systems.

Topic

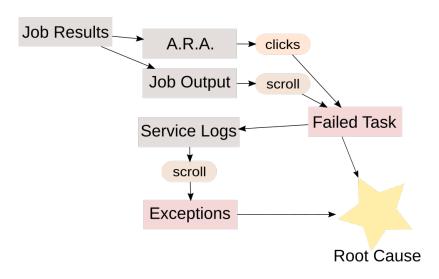
- Introduction
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Notes:

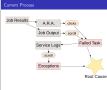
• This section introduces the goal of anomaly detection in CI logs.

Current Process



Anomaly Detection in CI Jobs —Introduction

└─Current Process



Notes:

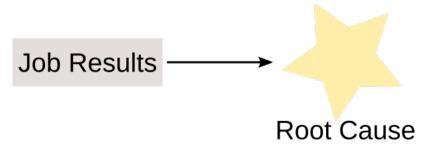
- This diagram shows the current actions a developper usually does to understand why a job failed.
- This process is tedious and time consuming and usually involves lots of clicking and scrolling. . .

Demo:

- Find a random change with a failed job.
- Demonstrate A.R.A.
- Try to figure out why it failed

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What if the machine looked for the errors?



Anomaly Detection in CI Jobs

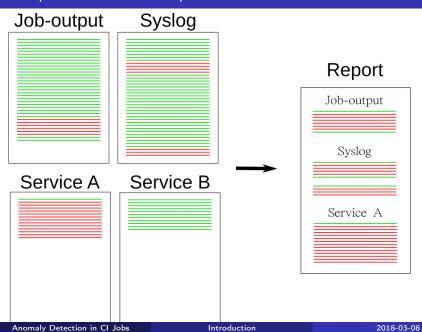
Introduction

What if the machine looked for the errors?



- Most of this process can be automated.
- $\bullet\,$ Automatic anomaly detection may greatly reduces investigation time.

And produced a nice report?



Anomaly Detection in CI Jobs

—Introduction

And produced a nice report?



Notes:

6 / 35

- Moreover, the machine can produce a nice report.
- Anomalies can be spread accross multiple log files.
- Only a small fraction of the log files are useful to understand a failure.

Base Principle

- Baseline: previous job logs
- Target: failed job logs
- Anomaly: new lines missing from the baseline



- Anomalies are defined as novelties from previous runs.
- Thus, comparing a failed job with a successful job usually yields anomalies.
- Next, we will see how machine learning methods can be applied to this challenge.

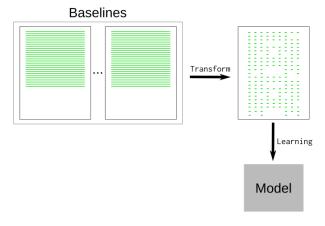
Topic

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- This section introduces two objects that can be used with CI logs:
 - the HashingVectorizer processor; and
 - the NearestNeighbor model.
- Note that other models may easily be used while keeping the same generic workflow.

Generic Training Workflow



Anomaly Detection in CI Jobs

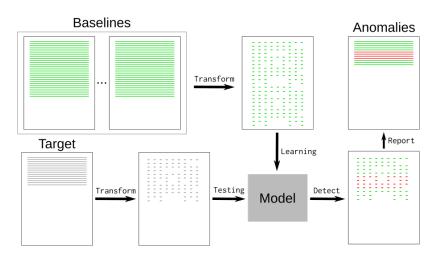
Learning Machine

Generic Training Workflow



- This diagram shows how baselines are processed to train a model.
- The raw text lines need to be converted before being used by a machine learning model.

Generic Testing Workflow



Anomaly Detection in CI Jobs

Learning Machine

Generic Testing Workflow



Notes:

• After the model is trained, we can repeat the same process to test the target and extract the novelties.

Hashing Vectorizer

Mar 11 02:43:28 localhost sudo[5195]: pam_unix(sudo:session): session opened for user root by (uid=5)

↓ tokenization

DATE localhost sudo pam_unix sudo session session opened for user root by uid

↓ hashing

hash(DATE) hash(localhost) hash(sudo) hash(pam_unix) hash(sudo) hash(session) ...

↓ sparse matrix encoding

[0, ..., 0, 1, 0, ..., 0, 1, 0, ...]

Anomaly Detection in CI Jobs

Learning Machine

☐ Hashing Vectorizer

	(Vectorizer
Nov 12 02:4	528 localitest sudd(\$195): part, aniejsudo session(: session operad for user rook to
	tokentration
- 1	DATE becallest sude part, unit sude session session opered for user ned by uit
	hashing
Pain	dr(DETS) had (locations) hash(sado) had (sam_umis) had (sado) had (sensor)
	sparse matrix encoding
	[8,, 0, 1, 0,, 0, 1, 0,]

Notes:

2018-05-22

- The first step of the workflow is to transform raw log lines into something more convenient for machines.
- The raw data can't be used because it's noisy: it contains random parts that would yield false positives.
- Let's use simple tokenization and a hashing vectorizer to transform the data.
- The sparse matrix is a numeric array of all possible hashes (2**20 by default).
- Each vector is very sparse as it only contains the token hashes.

Noise Reduction

• Random words may be replaced with known tokens:

Loken	Raw text
DATE	months/days/date
RNGU	uuid
RNGI	ipv4/ipv6/mac
RNGN	words that are 32, 64 or 128 char long
11 11	all numbers and non letters

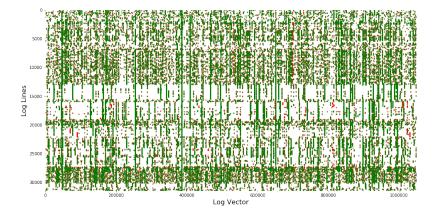
Anomaly Detection in CI Jobs -Learning Machine └─Noise Reduction

Random words may be replaced with known tokens

RNGU uuid

RNGI ipv4/ipv6/mac RNGN words that are 32, 64 or 128 char long all numbers and non letters

Example of Devstack Vectors



Anomaly Detection in CI Jobs

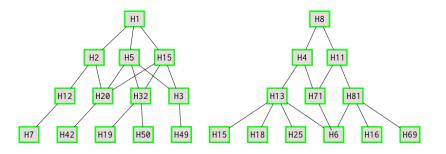
Learning Machine

Example of Devstack Vectors



- This example shows the vectors of a devstack job-output of 34k lines.
- The green dots show baseline vectors.
- The red dots show target vectors.
- This representation shows all the vectors in order, though we will look for the distances of each target vector to any baseline vectors.
- We can use a learning model to detect the red dots.

Nearest Neighbors Unsupervised Learner



Anomaly Detection in CI Jobs

Learning Machine

Nearest Neighbors Unsupervised Learner



Notes:

2018-05-22

- Nearest Neighbors learns from baseline vectors.
- This builds a tree of connected tokens.
- This doesn't hold the whole dataset.

kNeighbors computes vector's distance

```
2018-02-22 00:18:03.959599 | controller | "ephemeral_device": "VARIABLE IS NOT DEFINED!

Vector = controller | ephemeral_device | VARIABLE | IS | NOT | DEFINED |

kneighbors(Vector) = 0.9
```

Anomaly Detection in CI Jobs

Learning Machine

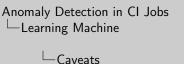
kNeighbors computes vector's distance



- This example illustrates an anomaly from the previous devstack example.
- The Nearest Neighbors model quickly computes the distance of a new vector to the baseline.

Caveats

• Need DEBUG in baseline logs.





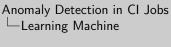
Notes:

2018-05-22

- This method relies on the fact that the baseline contains all non-anomalous data. Anything that can't be found in the baseline will be reported as anomalous.
- For example, *testr* logs only contains 'SUCCESS' when they succeed, and all the logs are only emited when the job fails.
- The example shows that both lines have the same distance, though we are only interested in the "pcre disabled" one.
- The next section introduces the log-classify tool, an implementation of this method.

Caveats

- Need DEBUG in baseline logs.
- Noise may hide important information:



└**C**aveats



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Caveats

- Need DEBUG in baseline logs.
- Noise may hide important information:

• Tokenization may need adjustment for small dataset.



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- Note: the project is actually incubated as logreduce.
- A log-classify projects has been proposed to make this part of the regular openstack-infra or zuul tooling, but the integration details remain to be defined.

Installation

• Use the container image or install using:

```
sudo dnf install -y python3-scikit-learn python3-aiohttp
sudo dnf install -y python3-pip
pip3 install --user logreduce
```

Anomaly Detection in CI Jobs
Introducing log-classify
Installation

. Use the container image or install using:

sudo dnf install -y python3-scikit-learn python3-siohttp sudo dnf install -y python3-pip pip3 install --user logreduce

Compare 2 files

• Output distance | filename:line-number: anomaly

```
$ pushd 01-files/
```

- \$ logreduce diff dib-success.log dib-failure.log
- 0.250 | dib-failure.log:2258: Package python-setuptools-0.9.8is obsoleted by python2-setuptoo

Anomaly Detection in CI Jobs
—Introducing log-classify

Compare 2 files



Notes:

- The first number tells the distance.
- Logreduce includes some contextual lines, by default 3 lines before and 1 line after the anomaly. This can be changed using *-context-length* command line argument.

- Go to the 01-files dataset.
- Use the logreduce diff command to extract the anomalies from the failure logs.

Compare 2 files

\$ pushd 01-files/

• Output distance | filename:line-number: anomaly

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```

Multiple baselines can be used

Anomaly Detection in CI Jobs
—Introducing log-classify

Compare 2 files

Output distance | filename:kno-number: anomaly
 Numbel 01-613ee/

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Multiple baselines can be used

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- Go to the 01-files dataset.
- Use the logreduce diff command to extract the anomalies from the failure logs.

```
Anomaly Detection in CI Jobs
   Introducing log-classify
         -Compare 2 directories
```

```
$ logreduce --debug diff success-*/ failure-*/ \
```

```
$ pushd 02-dirs/
```

```
$ logreduce --debug diff success-*/ failure-*/ \
            --html report.html
```

```
Classifier - Training took 84.141 seconds to ingest 33.4
Classifier - Testing took 173.464 seconds to test 22.952
```

99.67% reduction (from 128882 lines to 424)

Notes:

- In this second example, we use an html report to better see multiple files.
- A model is built per file. The model name is a minified version of the filename to include variations, e.g. audit.1 and audit.2 use the same model.
- "Loading" and "Testing" debug shows the model-name: used for each file.
- Before printing the anomalies, the baseline sources are also displayed, see the *compared* with debug.

- Go to the 02-dirs dataset
- Compare the job-output and notice it's not enough
- Run the diff command on the two directories with an html report logs
- Open the report.html

Model Training

• Model can be trained offline first:

```
$ logreduce dir-train sosreport.clf sosreport-good/ other/
INFO Training took 1.696 seconds to ingest 0.513 MB
$ du --si sosreport.clf
66k sosreport.clf
```

To be used later:

```
$ logreduce dir-run sosreport.clf sosreport-customer/
0.000 | ansible.log:0012: TASK [Command with long output]
0.626 | ansible.log:0014: fatal: [localhost]: FAILED!
0.364 | syslog:1576: localhost: System clock wrong by 1.417479
99.62% reduction (from 1595 lines to 2)
```

Anomaly Detection in CI Jobs

Introducing log-classify

└─Model Training

• To be used later:

\$ logreduce dir-rum soureport.clf soureport-customer/
0.000 | amsible.log:0012: TASK [Command with long output]
0.226 | amsible.log:0014: fatal: [localhost]: FAILED)
0.364 | syslog:1576: localhost: System clock wrong by 1.417479

\$ logreduce dir-train sosreport.clf sosreport-good/ other/ INFO Training took 1.696 seconds to ingest 0.513 MB

. Model can be trained offline fire

\$ du --si sosreport.clf 66k sosreport.clf

Notes:

• The Nearest Neighbor Tree of the sparse matrix is very small compared to the raw data.

Journald

- Extract novelty from the last day:
- \$ logreduce journal --range day
 - Build a model using last month's logs and look for novelties in the last week:
- \$ logreduce journal-train --range month journald.clf
- \$ logreduce journal-run --range week journald.clf



Notes:

• The journald range sets baseline as the previous day/week/month and the target as the current day/week/month.

Zuul Jobs

Build a model

```
$ logreduce job-train model.clf
```

- --job devstack
- --include-path logs/
- --pipeline gate
- --project openstack-dev/devstack
- --zuul-web http://zuul.openstack.org/api

Re-use the model

\$ logreduce job-run model.clf http://logs.openstack.org/...

Anomaly Detection in CI Jobs

Introducing log-classify

7 uul Jobs



Notes:

- -pipeline can be used to restrict baseline discovery to a specific pipeline
- -project can be used to restrict baseline discovery to a specific project. For example tox-py35 jobs likely need to be trained per project.
- -count specifies the number of previous jobs to use as training data.
- *-include-path* tells logreduce to fetch job artifacts in the logs/ directory.

DEMO:

• pick a job that failed and run "log \$logurl" command.

Zuul Jobs

Build a model

```
$ logreduce job-train model.clf
```

- -- job devstack
- --include-path logs/
- --pipeline gate
- --project openstack-dev/devstack
- --zuul-web http://zuul.openstack.org/api

Re-use the model

```
$ logreduce job-run model.clf http://logs.openstack.org/...
```

- Extract anomalies from a job result:
- \$ logreduce job http://logs.openstack.org/...

Anomaly Detection in CI Jobs Introducing log-classify └─Zuul Jobs \$ logreduce job-run model.clf http://logs.openstack.org/

Notes:

• -pipeline can be used to restrict baseline discovery to a specific pipeline

-- job devatack -project openstack-dev/devstack -zunl-web http://zunl.openstack.orw/api

· Extract anomalies from a job result: \$ logreduce job http://logs.openstack.org/

- -project can be used to restrict baseline discovery to a specific project. For example tox-py35 jobs likely need to be trained per project.
- -count specifies the number of previous jobs to use as training data.
- -include-path tells logreduce to fetch job artifacts in the logs/ directory.

DEMO:

pick a job that failed and run "log \$log_{url}" command.

Zuul Jobs Example: tempest-full

• Model trained with:

```
$ logreduce job-train tempest.clf
    --job tempest-full
    --include-path controller/
    --count 3
    --zuul-web http://zuul.openstack.org/api
```

Usage:

Anomaly Detection in CI Jobs Introducing log-classify

└─Zuul Jobs Example: tempest-full

```
| And hole Trained tempest full
| Model trained with tempest full
| I agreedles | pin-tails tempest full
| I agreedles | pin-tails tempest full
| I agreedles | pin-tails full
| I agreedl
```

Notes:

• We are going to use the tempest-full job as a case study.

- Go to the 03-jobs dataset.
- If there is enough time, attendees can build a model for another job. Otherwise, run the model with the pre-loaded logs.

Command line interface summary

- Supports directories, journald and Zuul jobs.
- Model can be trained dir-train, jounal-train and job-train.
- Model can be re-used: dir-run, journal-run and job-run.
- Or all in one command: dir, journal and job.

Anomaly Detection in CI Jobs

Introducing log-classify

Command line interface summary

- Supports directories, journald and Zuul jobs.
 Model can be trained directorin investerain and
- Model can be trained dir-run, journal-run and job
 Model can be re-used: dir-run, journal-run and job
 Or all in one command: dir, journal and job

Notes:

• Next section introduces integration in Zuul CI workflows.

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Notes:

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- Using the tool manually may be cumbersome.
- We will now see different ways to integrate anomaly detection in a CI workflow.

www.softwarefactory-project.io



Anomaly Detection in CI Jobs

Integration in CI Workflow

—www.softwarefactory-project.io

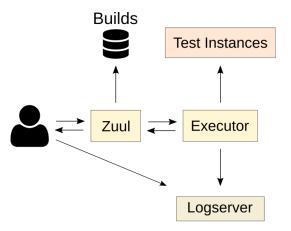


Notes:

2018-05-22

- Logreduce has been created in the context of Software Factory.
- It is a development forge that integrates many component to be easily deployed on premise or as a service.
- The architecture is modular and the screenshot shows some of the ready-to-use components.
- Logreduce is being used to analyze sf-ci logs.

Zuul Architecture



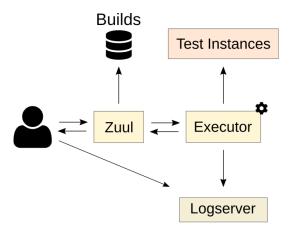
Anomaly Detection in CI Jobs —Integration in CI Workflow

└─Zuul Architecture



- This diagram shows the basic zuul workflow.
- Jobs are executed on ephemeral test instances.
- The executor retrieves the logs and publishes them to a logserver.
- Zuul returns the logserver url to the user.
- Zuul stores build information in a database. This is the key component to make the log-classify process possible.

Post-Run Analysis



Anomaly Detection in CI Jobs —Integration in CI Workflow

└─Post-Run Analysis



- This diagram shows the log-classify process running on the executor node.
- Pros: users/job doesn't have to be adapted, the post-run can be added to the base job.
- Cons: memory/cpu overhead on shared resources.

Post-Run Playbook

```
- job:
   name: base
   post-run:
      - upload-log
      - clasify-log
- tasks:
  - name: Fetch or build the model
    command: log-classify job-build ...
  - name: Generate report
    command: log-classify job-run ...
  - name: Return report url
   zuul_return: {zuul: url: log: ...}
  - name: Upload model
    synchronize: ...
```

Anomaly Detection in CI Jobs

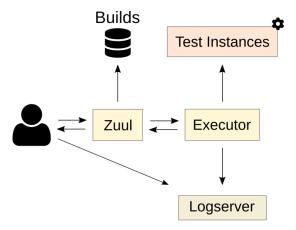
Integration in CI Workflow

Post-Run Playbook

```
Post Run Playbook

- juli:
- mans have
- pulse |
- quind-log
- clastify-log
- clastify-log
- tames |
- tame |
- tame |
- tames |
- tames
```

Post-Run Analysis running on test instances



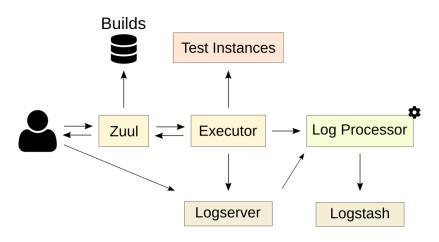
Anomaly Detection in CI Jobs Integration in CI Workflow

Post-Run Analysis running on test instances



- The same playbook could run on the test instance.
- Pros: doesn't cause memory/cpu overhead on shared resources.
- Cons: test instances need the tooling pre-installed.

Logstash Filter



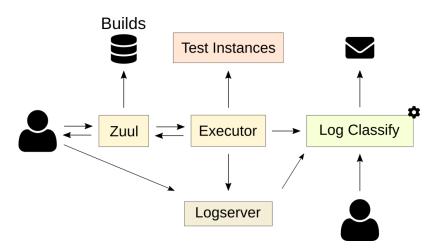
Anomaly Detection in CI Jobs —Integration in CI Workflow

Logstash Filter



- This diagram shows a more advanced Zuul workflow including a log-processor.
- The log-classify could be used as a library to add distance values to logstash events.
- Cons: the users need to wait and go to Kibana to get the report.

Standalone Service



Anomaly Detection in CI Jobs Integration in CI Workflow

_Standalone Service



Notes:

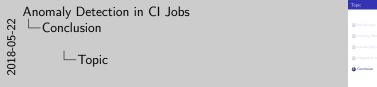
- The log-processor could be adapted as a standalone service (TBD).
- Could interface with elastic-recheck.
- This would enable user interaction, for example:
 - Trigger manual analysis
 - Feedback false-positive
 - ...

DEMO:

• Show a softwarefactory-project.io sf-ci job report.

Topic

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Notes:

• And this concludes the workshop.

Credits

- Roadmap:
 - Bootstrap community project.

Anomaly Detection in CI Jobs
—Conclusion
—Credits

Gredits

Roadmap:

Bouterup teammonly project.

Notes:

• Thank you for your time!

Credits

- Roadmap:
 - Bootstrap community project.
 - Better supports more jobs.
 - Interface with elastic-recheck.
 - Integrate in openstack-infra.

Anomaly Detection in CI Jobs
Conclusion
Credits

Roadmap:
Bootstrap community project
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Interface with elastic-secheck
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Notes:

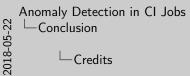
2018-05-22

• Thank you for your time!

Credits

- Roadmap:
 - Bootstrap community project.
 - Better supports more jobs.
 - Interface with elastic-recheck.
 - Integrate in openstack-infra.

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Credits

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Notes:

• Thank you for your time!