Log Anomaly Detection

on EuXFEL Nodes

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Introduction

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- **Log data** (LD) provides a detailed record of events, actions, and state changes.
- **Log anomaly detection** (LAD) identifies unusual patterns in LD that may indicate problems or issues.
- We show a **novel unsupervised log anomaly detection** approach tailored for the purpose of European XFEL watchdog logs using the sequential nature of the log messages.
- The EuXFEL watchdog log has some **features** which makes the problem challenging!

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> **Supervised deep learning models** require large labeled datasets, which are expensive and not always available.
> **Unsupervised methods** like clustering treat logs independently rather than sequentially, but missing contextual information.

...and we show an approach which can help with above stated problems!

Approach - Steps

1 **Preprocessing and tokenization**

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4 **Anomaly Detection**

Step 1 - Preprocessing and Tokenization

Some words appear only rarely, they should be eliminated (device names, numbers)

```
A problem ### with the XFEL/DEVICE 235
```

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1 Filter special characters,

`A problem with the XFELDEVICE 235`

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2. Substitute all potential names with one special symbol,

`A problem with the $name 235`

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`A problem with the $name $nz`

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(a, `problem`,`with`,`the`,`$name`,`$nz`)

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1. Filter special characters,
2. Substitute all potential names with one special symbol,
3. Numbers replaced with special symbols,
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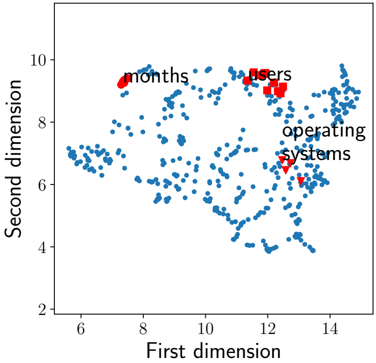
6. English stop words are removed (`a`, `the`, ...),

`(problem,$name,$nz)`

Step 2 - Embedding

We need a log entry represented as a vector.



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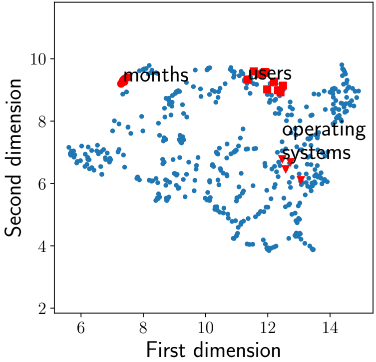

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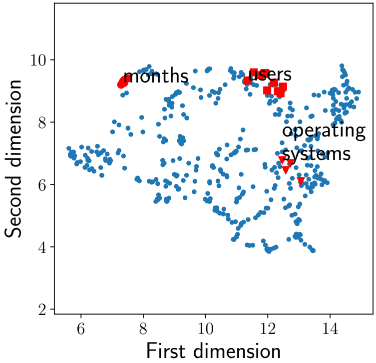
- Semantically similar words are represented with vectors that point to a similar direction

linear accelerator ↔ linac



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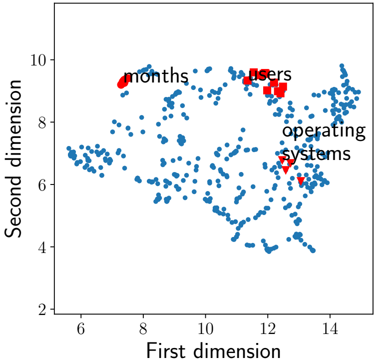

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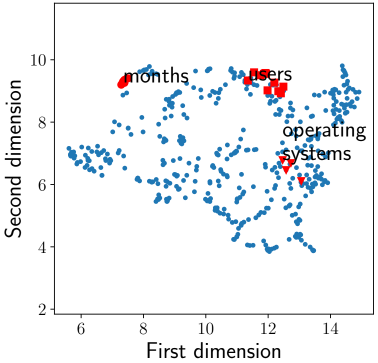

To represent a log entry `problem`,`$name`,`$nz`:

1 **Embedding** `[0.1,...]` `[2,...]` `[0.8,...]`

`problem` `$name` `$nz`

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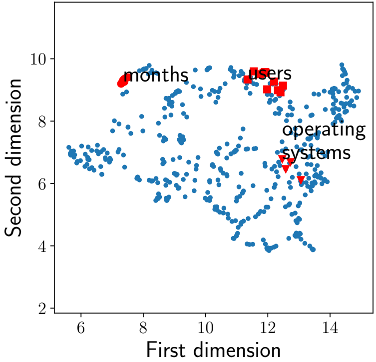

To represent a log entry `problem,$name,$nz`:

1. **Embedding** `[0.1,...] [2,...] [0.8,...]`
   `problem` `$name` `$nz`
2. **Summation** `[3.232,...]`

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- Low probability entries under learned HMM identified as anomalies.
- Detects anomalies from disruptions of expected patterns.

Step 3 - Modeling the Sequence - Features

Unsupervised	**No labels** needed, pure sequence modeling
Novelty	Handles **novel entries** based on contextual irregularity
Data	**Minimal number of parameters**
Robustness	Capable of flagging anomalies even if some are in training logs
Easy	With proper packages **10 lines** of Python code

Tiny Example

(TEST,OK,)

Tiny Example

(TEST,OK,TEST,OK,)

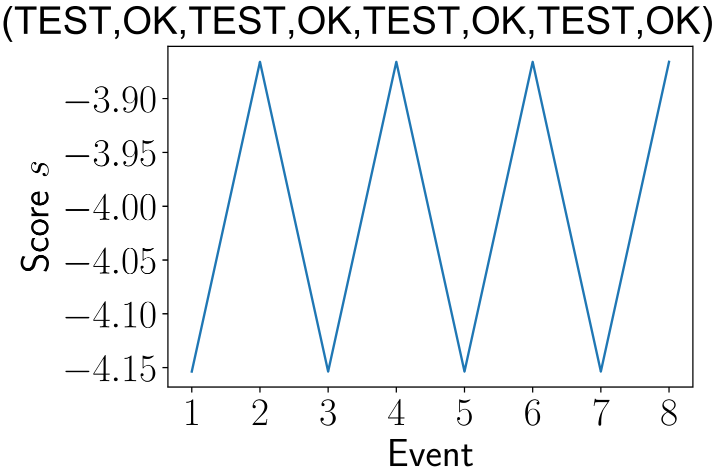
Tiny Example

(TEST,OK,TEST,OK,TEST,OK,   )

Tiny Example

(TEST,OK,TEST,OK,TEST,OK,TEST,OK)

Tiny Example



Tiny Example - Sequential Anomaly

(TEST,OK,)

Tiny Example - Sequential Anomaly

(TEST,OK,TEST,OK,)

Tiny Example - Sequential Anomaly

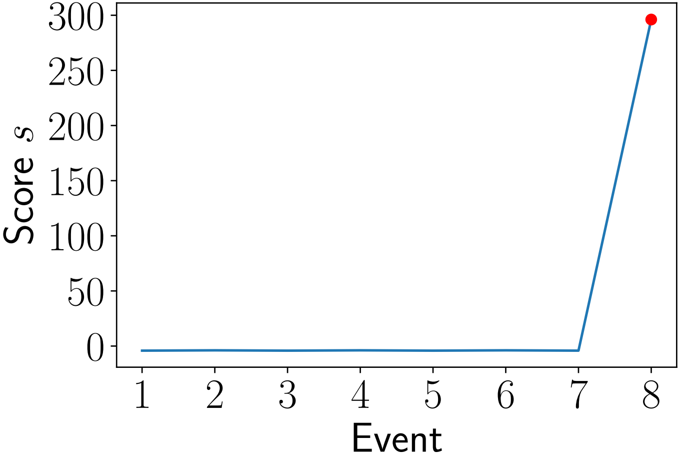
(TEST,OK,TEST,OK,TEST,OK,)

Tiny Example - Sequential Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**TEST**)

Tiny Example - Sequential Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**TEST**)



Tiny Example - Unexpected Message Anomaly

(TEST,OK,   )

Tiny Example - Unexpected Message Anomaly

(TEST,OK,TEST,OK,)

Tiny Example - Unexpected Message Anomaly

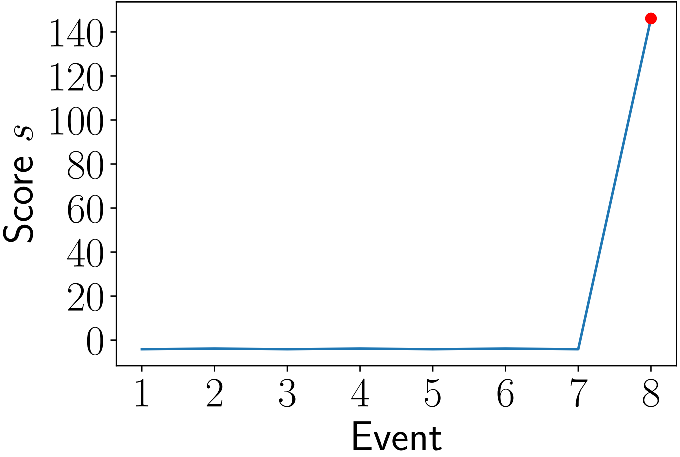
(TEST,OK,TEST,OK,TEST,OK,)

Tiny Example - Unexpected Message Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**ERROR**)

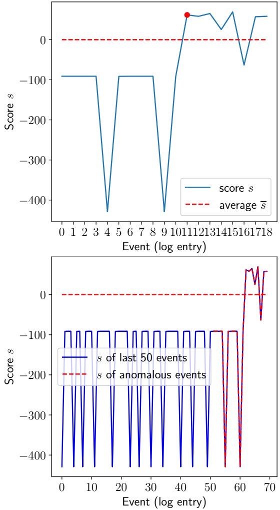
Tiny Example - Unexpected Message Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**ERROR**)



Example 1

```
⋮
0   remoteerrors errorcount $nz
1   remoteerrors errorcount $nz
2   remoteerrors errorcount $nz
3   remoteerrors errorcount $nz
4   remoteerrors errorcount $nz toggled $nz times $nz min
5   remoteerrors errorcount $nz
6   remoteerrors errorcount $nz
7   remoteerrors errorcount $nz
8   remoteerrors errorcount $nz
9   remoteerrors errorcount $nz toggled $nz times $nz min
10  remoteerrors errorcount $nz
11  rpccheck nullproc error
12  rpccheck fails $nz kill $nz
13  getpid pid not match process name
14  no process try start
15  getpid pid not match process name
16  pid change $nz $nz
17  rpccheck nullproc error
18  rpccheck fails $nz kill $nz
19  rpccheck fails $nz kill $nz
⋮
```



Example 2

⋮

```
0   remoteerrors errorcount $nz toggled $nz times $nz min
1   remoteerrors errorcount $nz
2   remoteerrors errorcount $nz
3   remoteerrors errorcount $nz
4   remoteerrors errorcount $nz toggled $nz times $nz min
5   rpccheck clnt create error
6   remoteerrors errorcount $nz
7   rpccheck fails $nz kill $nz
8   pid change $nz $nz
9   rpccheck fails $nz kill $nz
10  pid change $nz $nz
11  rpccheck fails $nz kill $nz
12  no process try start
13  pid change $nz $nz
14  remoteerrors errorcount $nz
15  no process try start toggled $nz times $nz min
16  remoteerrors errorcount $nz
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18  remoteerrors errorcount $nz
19  remoteerrors errorcount $nz
20  remoteerrors errorcount $nz toggled $nz times $nz min
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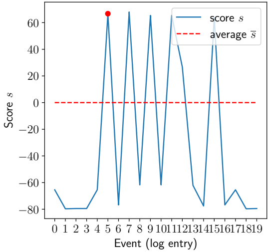
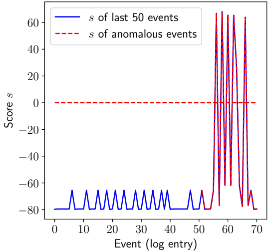
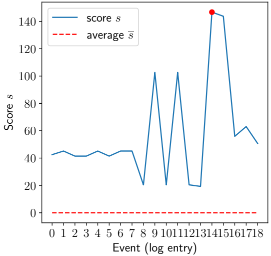


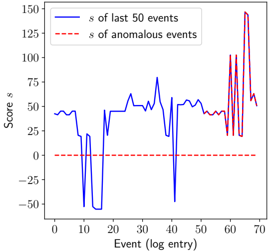


Example 3

⋮

0 getpid no process
1 no process try start
2 getpid no process
3 getpid no process
4 no process try start
5 getpid no process
6 no process try start
7 no process try start
8 pid change $nz $nz
9 getpid pid not match process name
10 pid change $nz $nz
11 getpid pid not match process name
12 pid change $nz $nz
13 pid change $nz $nz
14 **pid not match process name toggled $nz times $nz min**
15 pid not match process name toggled $nz times $nz min
16 signal term received
17 terminating threads closing files
18 writer thread terminated
19 interrupt thread terminated





Conclusion & Future Work

- The proposed method represents log entries as **word embeddings and models sequences** as HMMs to identify anomalies without labeled data.
- It detects **deviations from learned sequential patterns**.
- Results on logs from EuXFEL nodes show the approach can flag potential issues via score spikes corresponding to errors or disruptions.
- Challenges remain in **handling noise and minimizing false positives** in noisy logs.
- Future work could explore more advanced techniques and incorporate additional node statistics like **CPU/memory/network loads**
- The unsupervised sequence modeling approach enables detecting anomalies even when trained on logs containing anomalies, unlike supervised content-based methods. It focuses more on contextual irregularities than specific terms.

Thank you!

https://github.com/sulcantonin/LOG_ICALEPCS23

```python
from hmmlearn import hmm
import numpy as np

x = np.stack([[0,1],[1,0],[0,1],[1,0],[0,1],[1,0],[0,1],[1,0]])
model = hmm.GaussianHMM(n_components=2, covariance_type="diag")
model.fit(x[:-1,:])
logp = []
for i in range(1,x.shape[0]+1):
    logp.append(model.score(x[:i]))

logp = np.array(logp)
score = logp[:-1] - logp[1:]
```

Contact

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