Log Anomaly Detection

on EuXFEL Nodes

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Introduction

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- **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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- **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

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4 **Anomaly Detection**

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4 **Anomaly Detection**

```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:]
```

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,

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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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5. Tokenization.

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

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1. Filter special characters,
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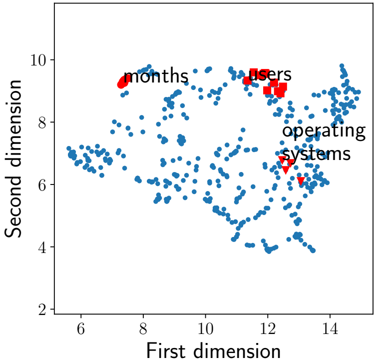
5. Tokenization.
6. English stop words are removed (`a`, `the`, ...),

`(problem,$name,$nz)`

Step 2 - Embedding

We need a log entry represented as a vector.



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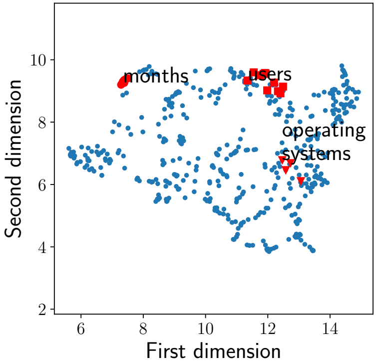
> Word2Vec takes a word and represents it as a vector based on context (adjacent words).



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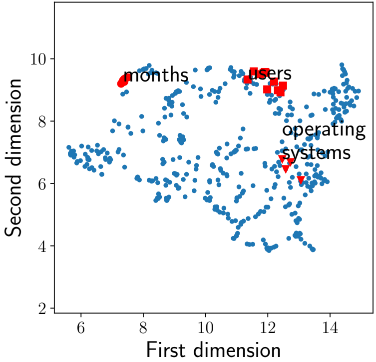
- Semantically similar words are represented with vectors that point to a similar direction
  linear accelerator ↔ linac



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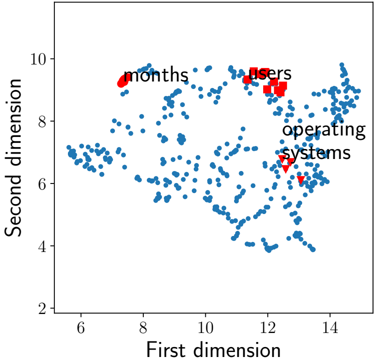

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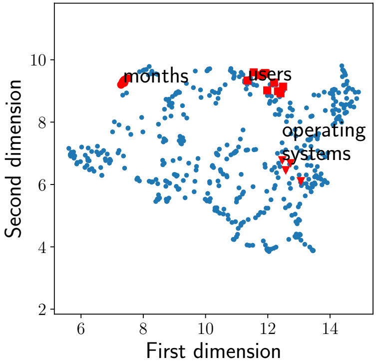

To represent a log entry `problem,$name,$nz`:

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

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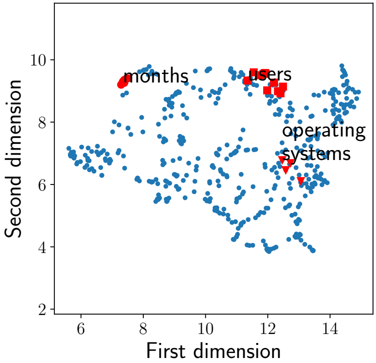

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1 **Embedding** `[0.1,...]` `[2,...]` `[0.8,...]`
`problem` `$name` `$nz`

2 **Summation** `[3.232,...]`

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$$
\begin{aligned}
s_i &= \log \frac{\text{prob. of prev.logs}}{\text{prob. of prev.logs + new one}} \\
&= \log \frac{p_\theta(o_1,\ldots,o_{i-1})}{p_\theta(o_1,\ldots,o_i)}
\end{aligned}
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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,)

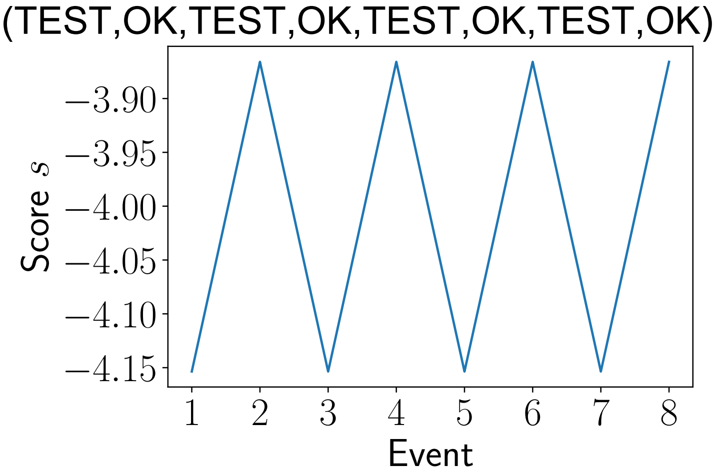
Tiny Example

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

Tiny Example

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

Tiny Example



Tiny Example - Sequential Anomaly

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Tiny Example - Sequential Anomaly

(TEST,OK,TEST,OK,   )

Tiny Example - Sequential Anomaly

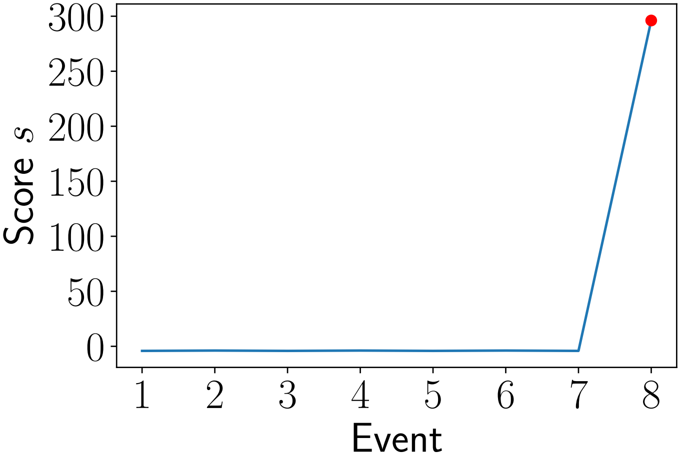
(TEST,OK,TEST,OK,TEST,OK,)

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

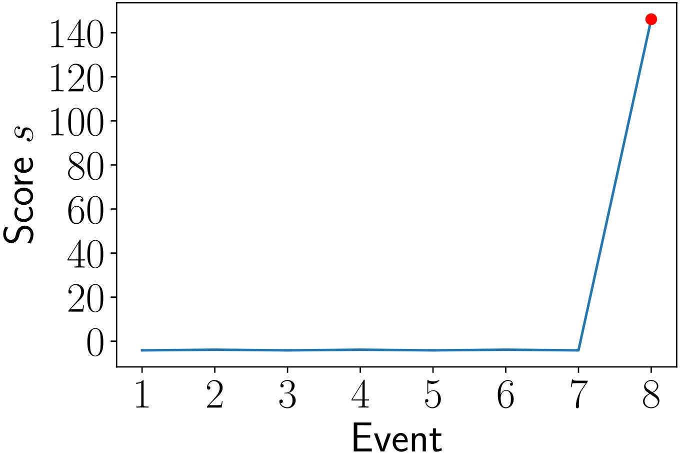
(TEST,OK,TEST,OK,TEST,OK,)

Tiny Example - Unexpected Message Anomaly

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

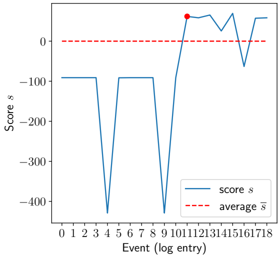
Tiny Example - Unexpected Message Anomaly

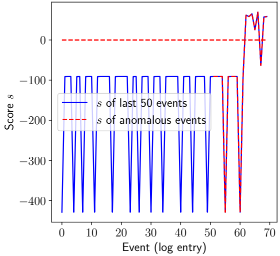
(TEST,OK,TEST,OK,TEST,OK,TEST,**ERROR**)



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
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17 remoteerrors errorcount $nz toggled $nz times $nz min
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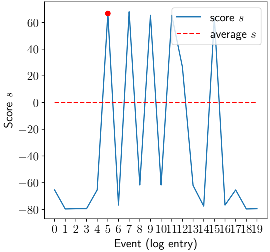
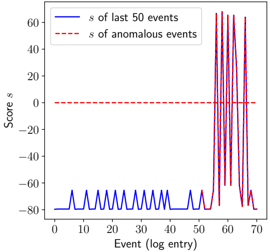
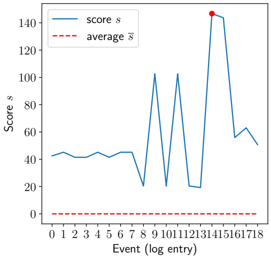


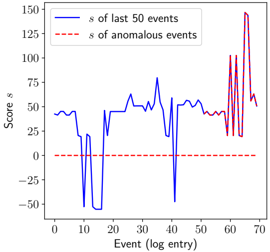


Example 3

⋮

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

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Contact

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