Anomaly Detection in Data Center IT Infrastructure using Natural Language Processing and Time Series Solutions

Elisabetta Ronchieri\textsuperscript{1,2}, L. Giommi\textsuperscript{1}, D. C. Duma\textsuperscript{1}, A. Costantini\textsuperscript{1}, D. Salomoni\textsuperscript{1}, F. Pacinelli\textsuperscript{2}

\textsuperscript{1}INFN CNAF, \textsuperscript{2}Univ. Bologna

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INFN CNAF Data Center in Bologna, Italy

- It focuses on technological development and knowledge transfer to heterogeneous experiments, national and European projects, and industry (whenever possible).

*Image provided by Pier Paolo Ricci, INFN CNAF.*

**Facts**
- over 1700 active users
- over 50 experiments
- over 65,000 CPU cores
- 41 PB of disk
- 98 PB of tapes
INFN CNAF Data Center Pillars

Pillars already supported

✓ Connectivity:
  to cloud and infrastructure for data transmission

✓ Security:
  for data and privacy protection

✓ ...

New Pillar

⚠ Intelligence
  - through infrastructure and algorithms in order to extract value from service and machine data and convert them into useful information
  - perform predictive maintenance
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Anomaly Detection through Logs and Monitoring Metrics

Facts
- large amount of data
- over 1,000 different services running
- data flowing 24/7

Goal
- perform predictive maintenance

How?
- define intelligence based on logs and monitoring metrics in order to detect anomalies and properly intervene
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Data Sources

Time range for this study: 6th June, 2020 - 21st July, 2021

**Log Files**
- 40 kinds of log files
- 1143 distinct machines

**Monitoring Metrics**
- 18 metrics
- 3 categories of monitoring metrics: io-stat, load average, and memory
Log Files and Monitoring Metrics

Log Files

- Logs are created by Linux system services and contain semi-structured texts.
- They are used to keep records of occurring events, analyze and debug system failures.
- The services may be highly verbose [Dec+20b].
- On a single machine, there are several different log files.
- Each log file corresponds to a distinct service.
- The log files have different formats.

Monitoring Metrics

- Each machine usually runs different services and we can collect information on:
  1. memory statistics, representing memory usage;
  2. the load the machine has been under, averaged over multiple time frames (i.e., load_avg);
  3. the central processing unit (CPU) statistics and input/output (I/O) statistics (i.e., io_stat).
# An Example of the ALRT Service Log File

<table>
<thead>
<tr>
<th>date</th>
<th>time</th>
<th>timestamp</th>
<th>hostname</th>
<th>ip</th>
<th>process_name</th>
<th>msg</th>
</tr>
</thead>
<tbody>
<tr>
<td>2020/08/11</td>
<td>11:57:17</td>
<td>1597139837.0</td>
<td>ddn-04-a.cnaf.infn.it</td>
<td>*</td>
<td>ALRT</td>
<td>ALRT CLI_MAIN Failing Disk 51P S/N JK1101YAJXPDEZ Reason(User Requested)</td>
</tr>
<tr>
<td>2020/07/08</td>
<td>14:36:39</td>
<td>1594211799.0</td>
<td>ddn-04-a.cnaf.infn.it</td>
<td>*</td>
<td>ALRT</td>
<td>ALRT AVR_MON Left Power Supply Failure</td>
</tr>
<tr>
<td>2020/07/08</td>
<td>14:36:39</td>
<td>1594211799.0</td>
<td>ddn-04-a.cnaf.infn.it</td>
<td>*</td>
<td>ALRT</td>
<td>ALRT AVR_MON Left Side AC Line Low</td>
</tr>
<tr>
<td>2020/07/25</td>
<td>12:24:08</td>
<td>1595672648.0</td>
<td>ddn-04-a.cnaf.infn.it</td>
<td>*</td>
<td>ALRT</td>
<td>ALRT DC_REC Failing Disk 42P S/N JK1101YAKAB69V Reason(IO Timeout)</td>
</tr>
</tbody>
</table>

- **date**, **time** and **timestamp** express when the instance has been registered in the local time zone.
- **hostname** and **ip** columns provide information on the machine and network on which the event occurred, respectively.
- **process_name** is the name of the service (log file).
- **msg** reports the textual message.

Log message

```
ALRT CLI_MAIN Failing Disk 51P S/N JK1101YAJXPDEZ Reason(User Requested)
```

Static field          Dynamic field
An Example of the memory.used Monitoring Metric

<table>
<thead>
<tr>
<th>name</th>
<th>tags</th>
<th>time</th>
<th>domain</th>
<th>duration</th>
<th>metric</th>
<th>value</th>
</tr>
</thead>
<tbody>
<tr>
<td>memory.used</td>
<td>host=api-int.cnsa.cr.cnaf.infn.it</td>
<td>1,62643E+18</td>
<td>cnsa.cr.cnaf.infn.it</td>
<td>0.22133</td>
<td>metrics-memory</td>
<td>1,37128E+09</td>
</tr>
<tr>
<td>memory.used</td>
<td>host=api-int.cnsa.cr.cnaf.infn.it</td>
<td>1,62644E+18</td>
<td>cnsa.cr.cnaf.infn.it</td>
<td>0.23058</td>
<td>metrics-memory</td>
<td>1,39689E+16</td>
</tr>
<tr>
<td>memory.used</td>
<td>host=api-int.cnsa.cr.cnaf.infn.it</td>
<td>1,62644E+18</td>
<td>cnsa.cr.cnaf.infn.it</td>
<td>0.22633</td>
<td>metrics-memory</td>
<td>1,46820E+16</td>
</tr>
<tr>
<td>memory.used</td>
<td>host=api-int.cnsa.cr.cnaf.infn.it</td>
<td>1,62644E+18</td>
<td>cnsa.cr.cnaf.infn.it</td>
<td>0.21558</td>
<td>metrics-memory</td>
<td>1,49160E+16</td>
</tr>
<tr>
<td>memory.used</td>
<td>host=api-int.cnsa.cr.cnaf.infn.it</td>
<td>1,62645E+18</td>
<td>cnsa.cr.cnaf.infn.it</td>
<td>0.21825</td>
<td>metrics-memory</td>
<td>1,49583E+16</td>
</tr>
</tbody>
</table>

- **time** expresses when the metric has been registered in the local time zone.
- **tags** and **domain** provide information about the machine values are collected.
- **name** and **metric** provide the metric name and category.
- **value** contains the metric value.
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Main Challenges

Working with

- Different types of data (textual and numerical);
- Thousands of machines to be analysed;
- A completely unsupervised task.
Methodology

**NLP**
- put text in lower case
- remove digits
- remove links
- remove punctionations and special characters

**AI**
- Principal Component Analysis
- Clustering Techniques
- Time Series Analysis

- K-Means
- DBSCAN

- split data from Service granularity to Machine granularity
- reorder data

**Final Results**
- for same machine and same technique, compare and combine conclusions close in time

**Log Dataset**

**Cleaning Process**

**Vectorizing Phase**
- vectorize message trough Word2Vec package

**Monitoring Data**
**Anomaly Dictionary**

**Approach:** The red highlights terms that may be likely anomalies [VRC22].
18 monitoring metrics are correlated.

Heatmap on the left shows how each pair of metrics is correlated.

Metrics are both positively and negatively correlated.

Selected one metric per class:
- \texttt{iostat.avg-cpu.pct_idle}, \texttt{load_avg.fifteen}, \texttt{memory.usage}
Principal Component Analysis (PCA)

**PCA**

- It is used to perform dimensionality reduction.
- PCA with reconstruction error RE allows us to recognize an anomalous observation.
- **Approach:** RE is larger for uncommon terms, so less observed observations.

Image shows a dimensional reduction to 2 components.
Clustering Algorithms

Density-Based Spatial Clustering of Applications with Noise

- **DBSCAN** builds clusters from the highly populated area of observations, close at most an *epsilon* value from each other.
- *epsilon* is computed performing parameter tuning
  - for log data, on overall distances between word-vectors
  - for monitoring metrics, by means of an elbow curve
- **Approach**: non-anomalous observations are expected to be concentrated closer to each other.

*K*-means

- **K**-means is a simple approach to partition data into *K* distinct, non-overlapping clusters.
- The only parameter is *K* that is computed performing parameter tuning.
- The observations have been partitioned among *K* clusters and then considered as potential anomalies provided belonging to the least populated cluster.
- **Approach**: expected large distances between anomalies and non-anomalies.
Anomaly Score (AS) - for log data

- For the entire message, AS is computed by doing the average value of the labels corresponding to the words that are part of the message.
- As this work is unsupervised, this process allows us to give a continuous measure of anomalies rather than a purely binary value, i.e. anomalous-non anomalous.
  - The binary value 0 or 1 for word represents respectively non-anomalous and anomalous terms.
- In the following, the words in red are the words identified as anomalous terms.

```
daily database available for update (local version: 26052, remote version: 26053)

  clean message

'daily', 'database', 'available', 'for', 'update', 'local', 'version', 'remote', 'version'

1 + 0 + 0 + 0 + 1 + 0 + 0 + 0 + 0 = 2/9 = 0.222
```
For log data

- Messages have been vectorized and word-vectors from each message have been averaged to get the vector belonging to the message.
- The difference between consecutive vector-messages has been calculated (measured in terms of Euclidean distance between vectors), thus obtaining a time-series of the differences between messages.

For monitoring data

- Metrics values have been standardized as the orders of magnitudes of the various metrics are really different from each other.

Approach: An interval of non-anomalous values is defined, including all the observations whose values are at most $s$ standard deviations $\sigma$ away from the value of mean $\mu$:

$$\text{threshold} = \mu + s\sigma, \; s \in [1, 3].$$

The sliding windows process is also considered to take overlapping subsets and detect anomalies.
An example of Mean and Variance Outlier Detection

A window size of 20 observations and tolerance of 2 standard deviations on a specific machine, i.e. cloud-ctrl01.
Validation Criteria

For log data

1. The anomaly score \( AS \) for each message has been considered, particularly the most recurring words in log messages with high/low \( AS \);

2. A similarity percentage of more than 20%/25% has been considered as an alarming sign.

For monitoring data

1. The Mann-Whitney test has been used to check for significant differences between anomalous and non-anomalous classified observations for every metric.
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An Example of Log and Monitoring Occurrences for a Given Machine
## Examples of Combining Results

<table>
<thead>
<tr>
<th>Service</th>
<th>Technique</th>
<th>Parameter</th>
<th>% of correspondence</th>
</tr>
</thead>
<tbody>
<tr>
<td>auditd</td>
<td>DBSCAN</td>
<td>$\text{eps} = 0.1$</td>
<td>50%</td>
</tr>
<tr>
<td></td>
<td>K-Means</td>
<td>$\text{n_clusters} = 3$</td>
<td>97.5%</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>$\text{thresh.} = 0.85%$</td>
<td>20%</td>
</tr>
<tr>
<td>smartd</td>
<td>DBSCAN</td>
<td>$\text{eps} = 0.1$</td>
<td>55%</td>
</tr>
<tr>
<td></td>
<td>K-Means</td>
<td>$\text{n_clusters} = 3$</td>
<td>53%</td>
</tr>
<tr>
<td></td>
<td>PCA</td>
<td>$\text{thresh.} = 0.85%$</td>
<td>55%</td>
</tr>
</tbody>
</table>

- Correspondence has been verified by checking logs and monitoring data occurring at less than 900 (15 minutes) seconds of difference.
- Anomalous and non-anomalous events are, at least to some extent, consistent in time.
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Discussions and Future Works

Discussions

- For log data, DBSCAN, K-means and Principal Component Analysis were very effective.
- For monitoring data, time series analysis provided interesting results, while treating messages as time-series observations did not show very meaningful results.
- We have got over 50% of correspondence between anomalous found in log files and monitoring metrics.

Future Works

- To analyse in more detail the anomalies’ nature in order to perform a more precise identification of the root causes of anomalies.
- To develop an advanced model, e.g. a deep learning one, that uses both types of data with respect to timestamp, machine name and network info.
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Elisabetta Ronchieri, elisabetta.ronchieri@cnaf.infn.it

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References I


References II


Appendix I

- A Subset of Monitoring Metrics
- Useful Parameters
# A Subset of Monitoring Metrics

<table>
<thead>
<tr>
<th>Category</th>
<th>Metric</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>load_avg</td>
<td>one</td>
<td>load average value of the machine every minute</td>
</tr>
<tr>
<td></td>
<td>five</td>
<td>load average value of the machine every five minutes</td>
</tr>
<tr>
<td></td>
<td>fifteen</td>
<td>load average value of the machine every fifteen minutes</td>
</tr>
<tr>
<td>memory</td>
<td>available</td>
<td>estimation of how much memory is available for starting new applications, without swapping</td>
</tr>
<tr>
<td></td>
<td>buffers</td>
<td>memory reserved by the operating system to allocate as buffers when the process needs them</td>
</tr>
<tr>
<td></td>
<td>cached</td>
<td>recently used files stored in RAM</td>
</tr>
<tr>
<td></td>
<td>dirty</td>
<td>memory waiting to be written back to disk</td>
</tr>
<tr>
<td></td>
<td>free</td>
<td>unused memory</td>
</tr>
<tr>
<td></td>
<td>total</td>
<td>total installed memory on the device</td>
</tr>
<tr>
<td></td>
<td>used</td>
<td>memory currently in use by running processes</td>
</tr>
<tr>
<td>iostat</td>
<td>pct_idle</td>
<td>the percentage of time that the CPU or CPUs were idle and the system did not have an outstanding disk I/O request.</td>
</tr>
<tr>
<td></td>
<td>pct_iowait</td>
<td>the percentage of the time that the CPU or CPUs were idle during which the system had an outstanding disk I/O request.</td>
</tr>
<tr>
<td></td>
<td>pct_nice</td>
<td>the percentage of CPU utilization that occurred while executing at the user level with a nice priority</td>
</tr>
<tr>
<td></td>
<td>pct_user</td>
<td>the percentage of CPU being utilization that while executing at the user level</td>
</tr>
</tbody>
</table>
Useful Parameters

Parameters

- **Dim. reduction**: if applicable, whether or not PCA was applied on data to reduce their dimension.
- **N. comps**: if applicable, (whether dimensionality reduction was applied), the number of principal components obtained.
- **N. clusters**: if applicable, the number of clusters defined for partitioning.
- **Window size**: if applicable, the length of the sliding windows (measured in a number of observations per partition).
- **Epsilon**: Estimating the Epsilon was very problematic as, potentially, every machine has its own optimal epsilon, whose computation is pretty tedious. The percentages refer to the quantile of the series obtained from the distance of all the observations (words) between each other.
- **Tolerance**: Tolerance has actually been different yet depending on the techniques in which it was adopted.

**N.A.**: Not Applicable, so that such parameter could not, or simply was not, specified in performing a certain algorithm.
## Hyperparameters Tuning with Grid Search Analysis Model

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Dim. reduction</th>
<th>N. comps</th>
<th>N. clusters</th>
<th>Window size</th>
<th>Epsilon</th>
<th>Tolerance</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBSCAN</td>
<td>TRUE, FALSE</td>
<td>2, 3, 10, 20</td>
<td>variable</td>
<td>N.A.</td>
<td>0.05%, 0.1%, 0.25%, 0.5%</td>
<td>N.A.</td>
</tr>
<tr>
<td>K-Means</td>
<td>TRUE, FALSE</td>
<td>2, 3, 10, 20</td>
<td>2, 3</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
</tr>
<tr>
<td>PCA Decomposition &amp; Recon-</td>
<td>implicit</td>
<td>2, 3, 10, 20, 30</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td>0.75, 0.85, 0.95 (measured as the quantiles of the error vector)</td>
</tr>
<tr>
<td>struction</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time-Series Outlier Detec-</td>
<td>N.A.</td>
<td>N.A.</td>
<td>N.A.</td>
<td>0, 10, 30, 60 (0 means no window partition)</td>
<td>N.A.</td>
<td>2, 3 (the k number of σ away from μ in the outlier detection alg.)</td>
</tr>
</tbody>
</table>