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Master Thesis

# Anomaly Detection in Infrastructure-agnostic Cloud Environments

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Matriculation Number: 1234567
July 14, 2020

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Assistant Supervisor
Your second Supervisor

Hereby I declare that I wrote this thesis myself with the help of no more than the mentioned literature and auxiliary means.

Berlin, July 14, 2020

. . . . . .
*(Signature [your name])*

**Abstract**

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On the one hand this PDF should give a guidance to people who will soon start to write their thesis. The overall structure is explained by examples. On the other hand this text is provided as a collection of LaTeX files that can be used as a template for a new thesis. Feel free to edit the design.

It is highly recommended to write your thesis with LaTeX. I prefer to use Miktex in combination with TeXnicCenter (both freeware) but you can use any other LaTeX software as well. For managing the references I use the open-source tool jabref. For diagrams and graphs I tend to use MS Visio with PDF plugin. Images look much better when saved as vector images. For logos and 'external' images use JPG or PNG. In your thesis you should try to explain as much as possible with the help of images.

The abstract is the most important part of your thesis. Take your time to write it as good as possible. Abstract should have no more than one page. It is normal to rewrite the abstract again and again, so probaly you won't write the final abstract before the last week of due-date. Before submitting your thesis you should give at least the abstract, the introduction and the conclusion to a native english speaker. It is likely that almost no one will read your thesis as a whole but most people will read the abstract, the introduction and the conclusion.

Start with some introductionary lines, followed by some words why your topic is relevant and why your solution is needed concluding with 'what I have done'. Don't use too many buzzwords. The abstract may also be read by people who are not familiar with your topic.

**Zusammenfassung**

# Contents

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# 1 Introduction

This chapter should have about 4-8 pages and at least one image, describing your topic and your concept. Usually the introduction chapter is separated into subsections like 'motivation', 'objective', 'scope' and 'outline'.

## 1.1 Motivation

The Internet is permeating almost every aspect of modern human life. Large numbers of online services ease our ways of retrieving information, purchasing goods and staying in contact with each other. New opportunities for businesses emerge with the availability of reliable and easy to use public cloud infrastructures. These cloud systems are environments which make it possible to abstract and share distributed hardware resources, allowing the operation of vast numbers of multiple simulated environments on hardware systems. Virtualisation allows the separate, yet simultaneous allocation of resources for various services at once.

As these cloud systems are becoming increasingly complex, they are getting harder to maintain and to operate, with system failures, outages and other unwanted behaviour occurring on a regular basis. Detecting such failures is indispensable for the correct, safe and reliable operation of complex systems, with the complete outage of the paying system of an E-Commerce shop for example, potentially resulting in high losses in revenue and the disruption of user experience. The software which operates these cloud environments, like most software, produces log data during execution - text-strings, which contain information about actions that have been performed, but can also indicate the state of a system at a given point in time. Log files can be used to conduct failure and anomaly analysis, and to help understand the root causes of failures and errors. System operators would examine logs manually and determine if certain log events can be linked to a given system failure. At the scale of mentioned systems, analysing such log files manually is infeasible. It is therefore necessary to develop automised methods for this purpose. Naive approaches like matching certain keywords (e.g. "*error*"), constructing a set of log lines indicating anomalies or regular expressions are not adequate to capture the complex nature of anomalies. For example, errors can happen, and can even be output explicitly as errors, but at the same time, it can be normal behaviour of a system to then automatically recover from given errors, so triggering an alarm is not wanted in these cases [1]. Traditional anomaly detection based on standard mining technologies cannot cope with the complex nature of anomalies in modern systems [2], since they are constantly evolving, which would require constant adjustments. Therefore, a more general approach is desirable.

This

## 1.2 Scope

The scope of this work is to find an appropriate way to represent dynamically changing log events using language models, and to assess their quality with regards to their ability of being utilised for solving the problem of anomaly detection. Therefore, an approach using an auto encoder to learn fixed length representations of log events that have been transformed into word embeddings with GloVe, is presented as baseline. Next, an approach to utilising word embeddings obtained from Bert are compared to those obtained from GPT-2 to use as input for a LSTM to learn error-free log sequences in a both supervised and unsupervised manner. For this purpose, three different ways of mapping the input of multiple log events to a target space, namely binary classification, multi-class classification and regression are evaluated.

## 1.3 Outline

The 'structure' or 'outline' section gives a brief introduction into the main chapters of your work. Write 2-5 lines about each chapter. Usually diploma thesis are separated into 6-8 main chapters.

This master's thesis is separated into 7 chapters.

**Chapter ??** is usually termed 'Related Work', 'State of the Art' or 'Fundamentals'. Here you will describe relevant technologies and standards related to your topic. What did other scientists propose regarding your topic? This chapter makes about 20-30 percent of the complete thesis.

**Chapter ??** analyzes the requirements for your component. This chapter will have 5-10 pages.

**Chapter ??** is usually termed 'Concept', 'Design' or 'Model'. Here you describe your approach, give a high-level description to the architectural structure and to the single components that your solution consists of. Use structured images and UML diagrams for explanation. This chapter will have a volume of 20-30 percent of your thesis.

**Chapter ??** describes the implementation part of your work. Don't explain every code detail but emphasize important aspects of your implementation. This chapter will have a volume of 15-20 percent of your thesis.

**Chapter ??** is usually termed 'Evaluation' or 'Validation'. How did you test it? In which environment? How does it scale? Measurements, tests, screenshots. This chapter will have a volume of 10-15 percent of your thesis.

**Chapter 6** summarizes the thesis, describes the problems that occurred and gives an outlook about future work. Should have about 4-6 pages.

# 2 Background

This chapter describes the technologies and terminologies that are most important for the proposed solution, and puts them into context.

In 2.1 a description of the term cloud computing is given. In 2.2 the theoretical foundation of deep neural networks is described, followed by an introduction to LSTMs. 2.4 gives insights on how natural language can be represented using language models. In 2.3 techniques on tackling the problem of anomaly detection with deep learning techniques are presented.

## 2.1 Cloud Computing

The term *cloud computing* usually refers to hardware and systems software in large data centres that provide a platform for applications delivered as services over the Internet. Due to the possibilities offered by clouds that are available in a pay-as-you-go manner, businesses with new ideas do not require enormous amounts of prefinancing in a hardly projectable amount of hardware and human operators to get their services online. It allows them to dynamically adapt to changing business needs without neither overcommitting hardware for services that do not turn out to be as intensely used as expected, nor undercommitting for a service that excels expectations, thus missing potential revenue, due to not being able to cope with the demand [3].

Virtualisation plays a vital role in modern clouds, offering the possibility for numerous users and their applications to share infrastructure in parallel, in contrast to conventional hosting, as depicted in figure 2.1. Through virtualisation, it is possible to achieve a better degree of utilisation of available hardware, for it allows a hardware server to run multiple software servers at the same time. Modern cloud services providers, like Amazon AWS or Microsoft Azure offer a vast number of different useful services, that can be provisioned flexibly and rapidly to the user, like allocation of task-specific hardware, different database types, object storage solutions or applications like analysis or management tools, as depicted in figure 2.2. End customers can be individual persons or businesses. While the services offered by public cloud providers are usually full-fledged and can be used by an end customer directly, the services offered by a cloud provider can also be integrated into a private cloud solution, thus resulting in a hybrid cloud, where workloads can be dynamically shifted between private and public clouds as costs and computing capacity needs change.

Making sure that these large numbers of services and virtual machines are operating correctly is a challenging task for the cloud service providers. It is therefore vital to keep records of program executions in the form of logs to be able to retrace errors that have

occurred.

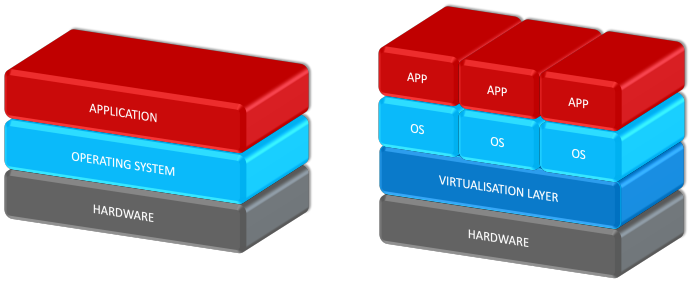



Figure 2.1: Traditional architeture vs. virtualised architecture

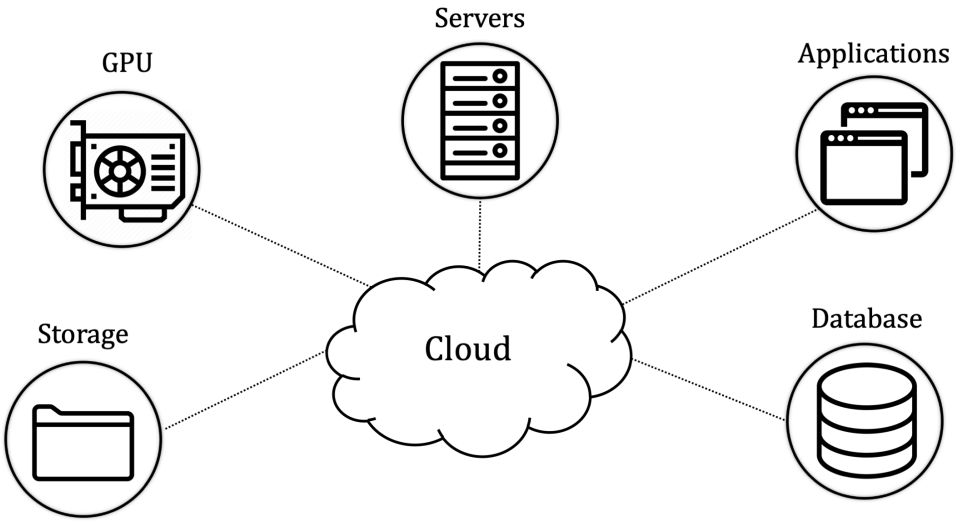



Figure 2.2: Traditional architeture vs. virtualised architecture

## 2.2 Deep Learning

### 2.2.1 Neural Networks

Neural networks are self-learning systems that constitute a subcategory of machine learning. By analysing training examples, it learns to compute a functional relationship between an input and an output [5]. Figure 2.3 is an illustration of a classical feed-forward

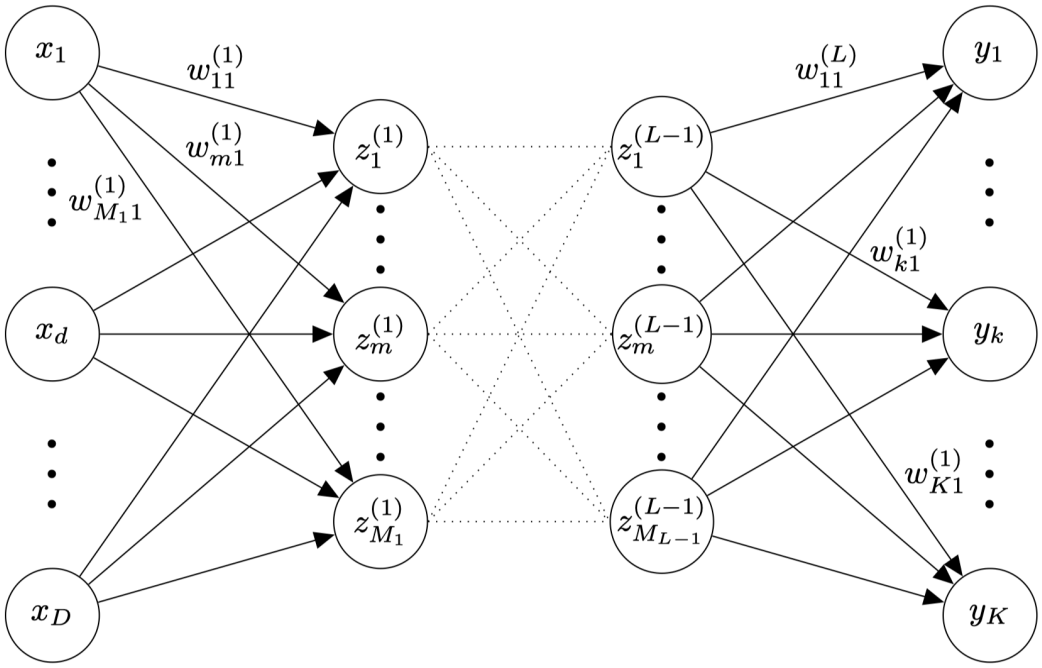



Figure 2.3: A neural network [4].

neural network. It consist of *neurons* and *weights* connecting the neurons. There are three types of neurons: Each input value maps to an *input* neuron depicted as $x_n$. *Hidden* neurons, depicted as $z_i$ are predictors created by mathematical functions and the *output* neurons, depicted as $y_k$ gather given predictions and compute the output [4]. Given data pairs $(x_1, t_1), ..., (x_N, t_N)$ with $x_n \in \mathbb{R}^D$ being input data, mapping to $D$ input neurons, and $t_n \in \mathbb{R}^K$ being target data. Each component $x_n$ is fed to one input neuron. If $L$ is the number of layers, then there are $L-1$ hidden layers. The network's latent variables of the hidden neurons are denoted by $z_m^{(l)}$. When data is being forwarded through the network, with the goal of obtaining a prediction from the network, the following formulas are relevant and describe every step through the network. The result of a complete forward propagation is denoted by activation 2.1:

$$a_j^{(l)} = \sum_{i=1}^{M_{l-1}} w_{ji}^{(l)} z_i^{(l-1)} = \mathbf{w}_j^{(l)^T} \mathbf{z}^{(l-1)} \tag{2.1}$$

On the result of this computation, an *activation function* is applied as in 2.2. There exists a variety of activation functions, depending on the use case. Activation functions transform the activation of output neurons as in 2.1 into an output signal [5]. For **regression** problems, the linear activation function $h(x) = x$ can be used. For **multi-classification** problems, where $t_n$ is a set of classes, the softmax function $\sigma(a)_j = \frac{e^{a_j}}{\sum_{k=1}^{K} e^{a_k}}$ is used [4].

There are more cases, but regression and multi-classification are the most relevant here, as they are used in chapter 3.

$$z_j^{(l)} = h_l(a_j^{(l)}) = h_l\left(\mathbf{w}_j^{(l)^T}\mathbf{z}^{(l-1)}\right) \tag{2.2}$$

If $l = 1$, then equations 2.3 and 2.4 hold:

$$a_j^{(1)} = \mathbf{w}_j^{(1)^T}\mathbf{x} \tag{2.3}$$

$$z_j^{(1)} = h_1\left(\mathbf{w}_j^{(1)^T}\mathbf{x}\right) \tag{2.4}$$

If $l = L$, then every $y_k$ can be obtained in the following way:

$$y_k = h_L(a_k^{(L)}) = h_L\left(\mathbf{w}_k^{(L)^T}\mathbf{z}^{(L-1)}\right) \tag{2.5}$$

The result $y_k$ of the computation of $x_k$ is then compared to the real value $t_k$ using an *error function*. Mean Squared Error $MSE = \frac{1}{n}\sum_{i=1}^{n}(t_k - y_k)^2$ can be used for regression problems, calculating the average squared difference between the estimated and the actual values, and Cross-Entropy $-\sum_{c=1}^{M} y_{o,c}\ \log(p_{o,c})$ for multiclass classification, calculating the separate loss for each class label per observation. The obtained values are then fed into the *back propagation algorithm*, updating weights $w_j$, thus trying to minimise the error.

### 2.2.2 LSTM networks

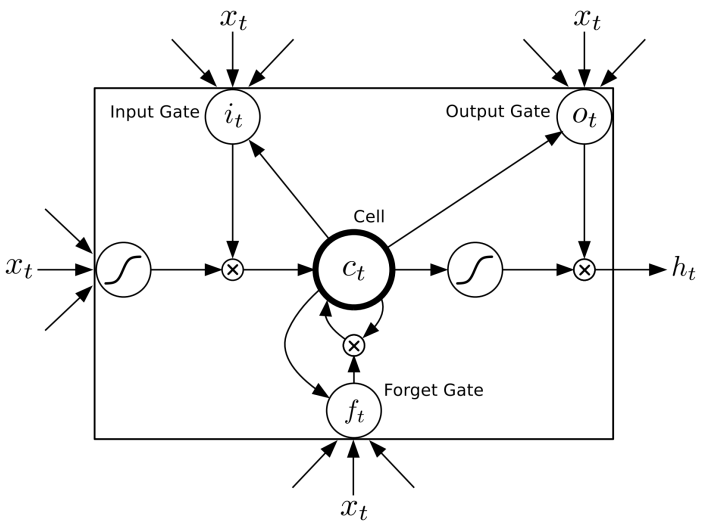



Figure 2.4: LSTM block [6]

Recurrent neural networks (RNN) with Long Short-Term Memory (LSTM) are a widely-used effective model to tackle learning problems on sequential data. Being a general model, they do not have be to be adapted to a specific problem like earlier methods, thus allowing them to produce state-of-the-art results for problems like language modeling [7], anomaly detection [2] amongst others.

The core of the LSTM architecture is memory cell which maintains its state over time, in combination with gating units, which control the information flow [8], allowing it to remove or add information. The traditional LSTM architecture was first described by [9]. The schematic structure of LSTM blocks is depicted in figure 2.4.

The first step is expressed through equation 2.6. It is a forget gate, which considers the previous hidden state input $h_{t-1}$ and the current input $x_t$, and outputs a vector of numbers between 0 (forget: value should be multiplied by 0) and 1 (keep: multiply value by 1), one for each element from the previous cell state $c_{t-1}$. Next, equation 2.7 computes, which values to update. Equation 2.8 creates a vector of candidate values $\hat{c}_t$ for the new state $c_t$. In equation 2.9, the previous state is multiplied with $f_t$, in order to keep or forget elements, adding the new candidate values $\hat{c}_t$ multiplied by the degree updating $i_t$. As the last two steps, in equation 2.10, the output is computed by applying a sigmoid on the cell state, to decide which parts to output. Then, in equation 2.11, a tanh is applied on the cell state $c_t$, which is multiplied by the output of the sigmoid gate $o_t$ [10] [6].

$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f) \tag{2.6}$$

$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i) \tag{2.7}$$

$$\hat{c}_t = \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{2.8}$$

$$c_t = f_t c_{t-1} + i_t \hat{c}_t \tag{2.9}$$

$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o) \tag{2.10}$$

$$h_t = o_t \tanh(c_t) \tag{2.11}$$

### 2.2.3 Bidirectional LSTM networks

In a sequence prediction task, in which one has access to both past and future input features for a given point in time, a bidirectional LSTM network as depicted in 2.5 can be applied as proposed by Graves et al. [6]. In this way, it is possible to make us of past features via the forward state and future features via the backward states. Forward and backward passes are executes similarly to

The forward and backward passes over the unfolded network over time are carried out in a similar way to regular network forward and backward passes, except that we need

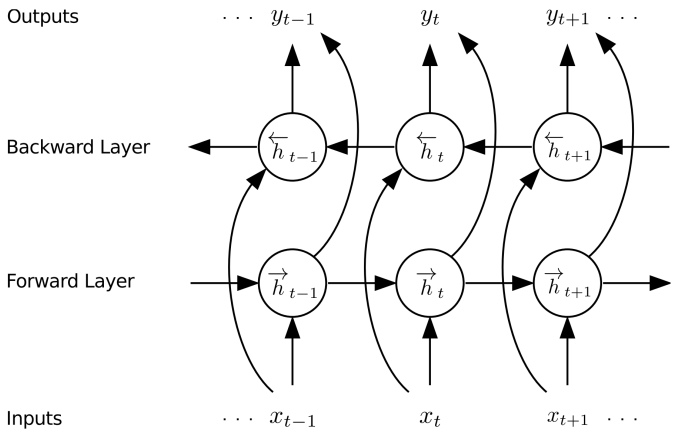



Figure 2.5: Bi-directional LSTM [6].

to unfold the hidden states for all time steps. We also need a special treatment at the beginning and the end of the data points. In our implementation, we do forward and backward for whole sentences and we only need to reset the hidden states to 0 at the begging of each sentence.

## 2.3 Anomaly Detection

*Anomaly detection* describes the general problem of finding subsets or patterns in data, that do not conform to a defined notion. These patterns are often referred to as outliers or anomalies.

Anomalies can arise in datasets for various reasons, like system errors, fraud or malicious activities. It often might appear to be straight-forward to define normal regions, and declare all data laying outside of these regions as anomalies. Unfortunately, finding these normal regions is in fact very difficult, since it might not always be possible to capture the nature of *normal* data in its completeness, due to lacking data or the unsharp border of normal and abnormal. Consider figure 2.7, which illustrates the presence of normal regions and anomalies in a dataset. The datapoints in the regions $D_1$ and $D_2$ are considered normal, since the majority of observations lie in these regions. Points that are sufficiently far away, like the points in regions $A_1$ and $A_2$ are considered anomalies. But consider also the points $B_1$. Should they be marked as normal or abnormal? Are the borders around $D_1$ and $D_2$ correct, or are they not sufficiently broad, due to the lack of enough normal training examples? Additionally to the difficulty of finding correct division of normal and abnormal, normal behaviour can be subject to constant evolution in a dynamic system, thus making previous definitions of *normal* behaviour wrong, obsolete or incomplete. Additionally, it is often hard or impossible to obtain labeled data for the desired domain, thus hindering the training and verification of a model [11].

Due to the difficulties arising from the aforementioned constraints, solutions to the problem of anomaly detection are usually very domain-specific, influenced by the form in which data is available, labeled or unlabeled and the form of anomalies which are to be detected. Solutions presented by researchers feature techniques from various fields, including data mining, statistics, machine learning which are applied to the domain in question [11]. Figure 2.6 outlines the central steps involved in finding an appropriate anomaly detection technique to a given problem.

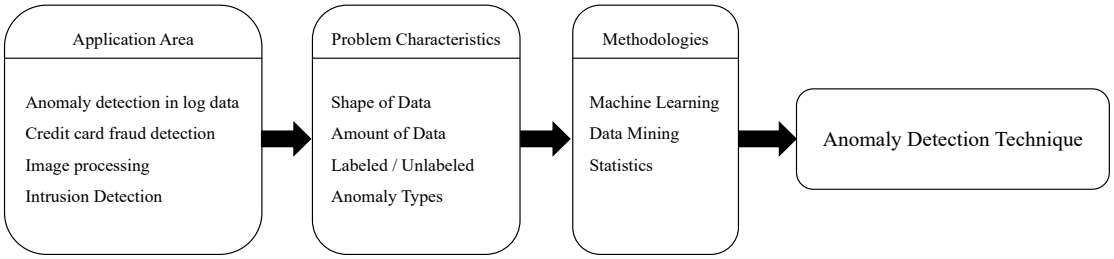



Figure 2.6: Schema of the development of an anomaly Detection technique [11].

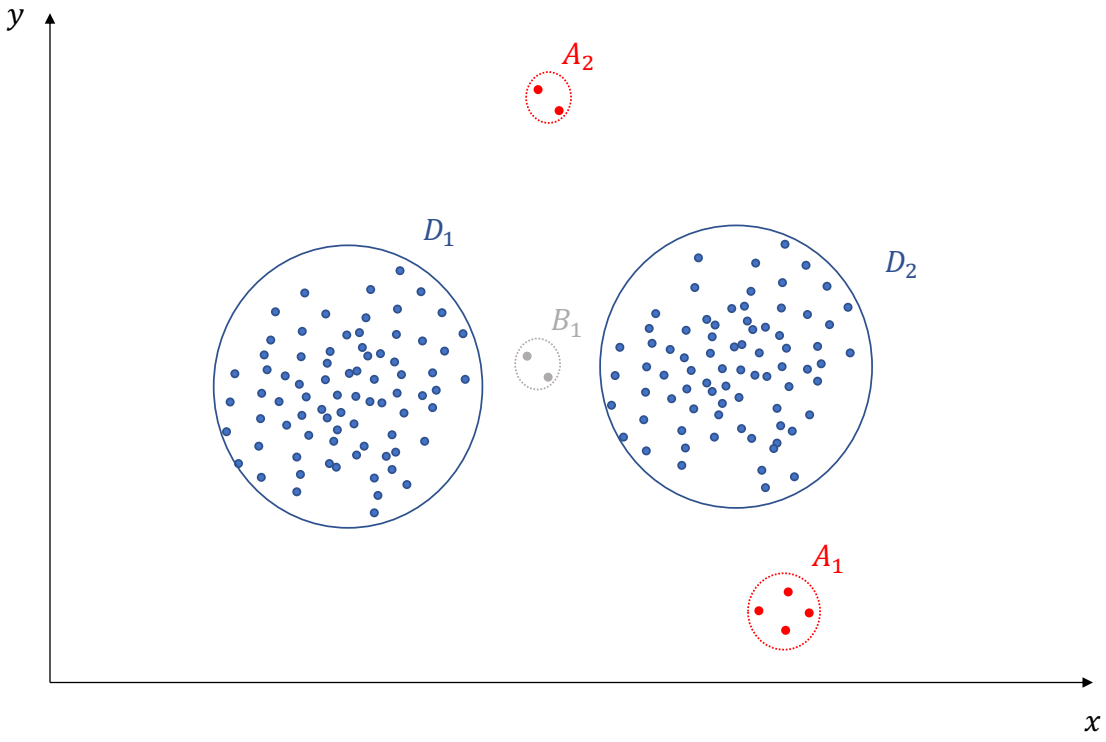



Figure 2.7: Example of anomalies in a dataset.

## 2.4 Natural Language Processing

Natural language processing (NLP) involves the engineering of computational models to solve practical problems in understanding human languages. Having initially relied on processing involving statistics, probability and machine learning, the recent boost in available computational power with GPUs, allowed deep learning to raise the bar for many NLP-tasks. NLP can be broadly divided into two categories, namely *base concepts* which deal with the fundamentals of understanding language, and concrete applications by means of these very concepts, although the border between the two is often fluent. Base concepts include *language modelling*, *morphological processing* (find segments within words), *syntactic processing* (how different words and phrases relate to each other within a sentence) and *semantic processing* (understanding the meaning of words), whereas applications include areas such as text translation, classification of documents, summarisation of texts, extraction of information and many more.

### 2.4.1 Word embeddings

Language modelling can be viewed as an essential piece of probably any practical application of NLP. Generally speaking, it involves creating a model to predict words given previous words by finding appropriate representations for words through analysing the relations of words within their context. Numeric vectors, which represent single words, obtained by language model techniques are called *word embeddings* [12]. For example, the word "Olympics" appears often in the context or close to words like "athlete", "running" or "tournament" but rather rarely next to words like "microphysics" or "chicken". These relationships can be translated into a vector that describes how the word "Olympics" is used within a language [13]. Word embeddings can be retreived either by Principle Component Analysis or by using deep neural network models and capturing their internal states.

### 2.4.2 Bert

The development of a language representation model will be outlined on the basis of Bert (**B**idirectional **E**ncoder **R**epresentations from **T**ransformers) by Devlin et al. [14]. The model architecture is a multi-layer bidirectional Transformer encoder. Training includes two steps: *pre-training* and *fine-tuning*. Pre-training involves training on unlabelled data over various pre-training tasks. Finetuning then uses the weights initialised with the parameters obtained from pre-training, re-calibrating them using labelled data.

For pre-training, they extract sentences from a large unlabelled corpus like English Wikipedia. The obtained sentences are then transformed into tokens, and separated by pre-defined separation symbols, `[CLS]` for the beginning of a sentence, `[SEP]` for the ending of sentences as illustrated in figure 2.8. They then proceed with the first task, namely Masked Language Model (MLM). For this purpose, they mask 15% of words with the special `[MASK]` token, and then predict these tokens. The second task is Next Sentence Prediction (NSP), where sentences `A` and `B` are separated with the

aforementioned `[SEP]` token, as it can be again seen in figure 2.8 are marked with the label `isNext` if `B` follows `A` or `notNext` if the following sentence is a random sentence, with both cases occurring 50% of the time. After the computationally expensive pre-training is done, taking 4 days of training on 16 cloud TPUs for one language [15], fine-tuning can be done on any downstream NLP task in at most one hour on one cloud TPU, for example the Stanford Question Answering Dataset (SQuAD v1.1) by Rajpurkar et al. [16], a collection of 100k crowd-sourced question/answer pairs, or the General Language Understanding Evaluation (GLUE) benchmark by Wang et al. [17], which involves various natural language understanding tasks.

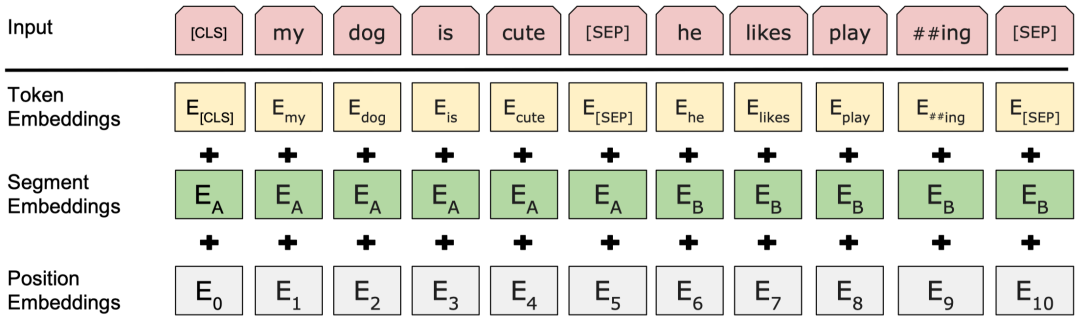



Figure 2.8: Bert

## 2.5 Log Parsing

Due to the unstructured nature of log data, the first crucial step in anomaly detection on log data is parsing. Raw log messages consist of a constant and a variable part, with the constant part remaining identical for every occurrence, while the variable part records runtime information and varies among different event occurrences. The goal of log parsing is to separate the *constant* and *variable* part of a raw log message [18][19]. Figure 2.9 shows how logging statements from Java source code are parsed. The logging statements variable parts `block`, `block.getNumBytes()` and `inAddr` are dynamically interpreted at runtime and replaced by their respective values. The resulting log message is then printed with additional customisable values (timestamp, logging level and component) by the respective logging framework. The structured log is then produced by the log parser, separating the constant part, which is also called a *template* (`Received block <*> of size <*> from /<*>`) from the variable parts (`blk_-562725280853087685, 67108864` and `10.251.91.84`), replacing the variable parts inside the constant parts with a pre-defined token - "`<*>`" in this example.

Log parsing is usually the first step in order to perform a log analysis task. Log parsing enables enables searching, filtering, grouping and mining of logs. Applications include usage analysis at Twitter [20] or workload modelling [21]. Logs can also be used as data

sources for performance modelling [22] where performance improvements of a system can be validated using log data. A very prominent application of log parsing is anomaly detection. Since logs record execution information of a system, they are a valuable data source for identifying abnormal behaviour of a system [19].

There exist offline and online log parsers, offline meaning that it first reads and analyses the whole dataset first before applying the parsing model, while online parsers adjusts the parsing model gradually during the parsing process [23]. Log parsers employ various concepts and techniques in order to parse logs - a few of them are summarised here:

- *Frequent Pattern Mining* involves finding sets of patterns, in this case templates, that appear frequently in a data set. The procedure can be outline as follows: Iterating over the log data several times, while building frequent sets of tokens, followed by grouping log messages in clusters, and then extracting event templates from each of the clusters.
- Log parsing can be viewed as a *clustering* problem. All approaches can be roughly outlined as clustering templates hierarchically based on a defined metric, for example the weighted edit distance between pairwise log messages [19].
- Some proposed methods utilise special heuristics, exploiting the unique characteristics of log messages. IPLoM first identifies frequent words occurring more frequently than a threshold value, then extracts combinations of these words that occur in each line in the data set, marking them as cluster candidates, and finally selecting the candidates the occur more often than a threshold value as clusters [24]. Drain employs a parse tree with fixed depth. It first preprocesses the incoming messages with regular expressions based on domain knowledge, then search a log group for that message, with log groups being leaf nodes. If a suitable group is found, it matches the message to that group, if not, then a new group is created [23].

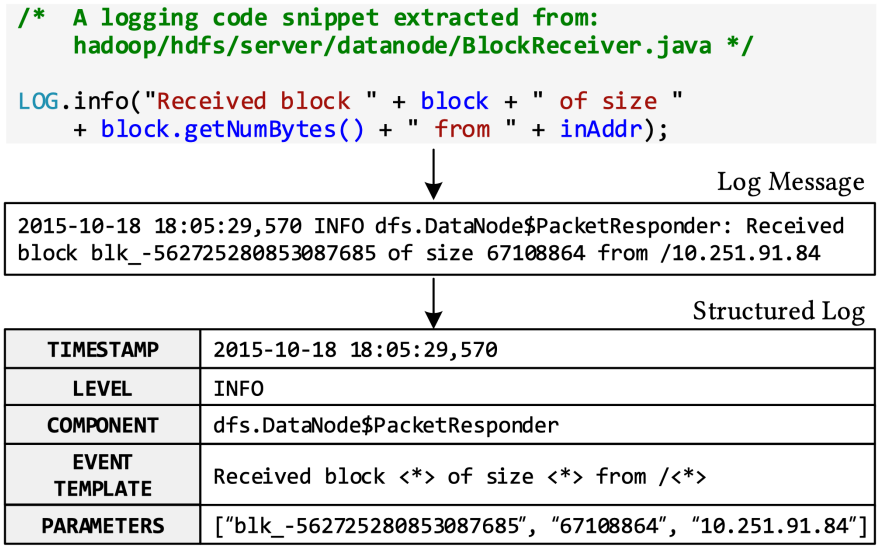



Figure 2.9: Schematic execution of log parsing [19]

# 3 Concept

Establishing a connection between the latest advances in NLP and anomaly detection in system log data is a recently emerged field in research. The need for using language models to convert log events into word embeddings emerges from the weaknesses of older anomaly detection approaches that are not flexible enough to cope with the complex nature of system log data. There exist difficulties in reusing previously obtained knowledge from training on data from a given dataset and transferring it to a differently structured dataset. Most proposed techniques for solving the problem of anomaly detection in system log data suffer from not being transferable and being non-resilient to changing log data. The objective of this work is to provide a means to automatically detect anomalies in logs that are potentially affected by processing noise and changes of log events by updates of the underlying software, and to transfer knowledge obtained from a dataset of log sequences to another dataset of logs with a transfer method.

In section 3.1, the general problem statement is given, and necessary requirements for this work are specified. In the following section 3.2, the overall system architecture with its components is outlined and visualised. In section **??** the developed approaches, including the baseline approach, are explained in detail. There exist three approaches, (1) the baseline approach featuring learning of sentence level log line representations with the help of an auto encoder on the basis of word level language representations and classification using regression, followed by the (2) regression and (3) multi-class classification approach using log line representations obtained by a language model which is able to transform log lines on sentence level. In section 3.5 the transfer learning mechanism is described in detail. In the final section 3.6 possible improvements of the proposed approach are presented.

## 3.1 Problem Statement and Prerequisites

Logs are print statements inside programs which are defined by a fixed sequence of code statements written by developers. The execution of a program is defined by these statements, and therefore follows a predetermined pattern. Hence, the produced logs must also follow certain patterns, chronological orders, and proportional relationships between number of occurrences of logs with each other. These logs must be first brought into an appropriate form, in .

### 3.1.1 Formal problem definition

A log is a sequence of ASCII characters, which is denoted by the set $\mathcal{A}$ that form unstructured messages $M = (m_0, m_1, ..., m_n)$ with every character of $m_i \in \mathcal{A}$. Log

messages consist of tokens - most tokens are English words, but do also include special characters. The number of tokens from which a log message can consist of, varies. Let $g : \mathcal{A}^i \rightarrow \mathbb{R}^w$ be a function that takes a variable length of $i$ tokens that make up a log message and maps them to a fixed length vector of dimension $w$. This is the function which represents the computation of embeddings. $E = (e_0, e_1, ..., e_n)$ is the sequence of vectors based on $M$, parsed and transformed into embedding representations. Let $\mathcal{B} = (b_0, b_1, ..., b_n)$ be the dataset where every $b_i \in 0, 1$ denotes if the log event represented by $e_i$ is anomalous (1) or not (0). $\hat{b_i}$ denotes the system's prediction for $b_i$.

*Multi-classification*: For every distinct log template, we assign $C = \{c_0, c_1, ..., c_k\}$ to be the set of distinct class keys. Let $g : |s| \times \mathbb{R}^w \rightarrow \mathbb{N},\ g(E_i, \Psi) = \mathbb{R}^k$ be a function computed by a neural network, that given a subsequence of $s$ vectors out of the dataset $E$, namely $E_i = (e_i, ..., e_{i+s})$, returns a probability distribution $Pr_i[e_{i+s+1}|E_i] = (c_0 : p_0, c_1 : p_1, ..., c_k : p_k)$, describing the probability for each template class from $C$ to appear as the next class at index $i + s + 1$, given $E_i$. The objective is to learn the parameters $\Psi$, so that for each fixed length sequence of vectors, the function predicts the correct subsequent class. If one of the top $q$ candidate classes matches the actual class, then $\hat{b_i} = 0$ is returned, if it does not match the actual class, $\hat{b_i} = 1$ is returned.

*Regression*: Let $h : |s| \times \mathbb{R}^w \rightarrow \mathbb{R}^w,\ h(e_i, s, \Phi) = d$ be a function computed by a neural network, that based on a sequence of $s$ vectors $E = (e_j, ..., e_{j+s})$ predicts the vector $d$ at index $j + s + 1$. The objective in this case is to learn parameters $\Phi$, so that the system predicts the vector following the sequence of vectors of length $s$. If the distance between the predicted vector $d$ and the actual vector $e_{j+s+1}$ is above or below certain threshold values, which will be computed by the q-th percentile of all loss values from the original dataset, then $\hat{b_i} = 1$ is returned, if it is inside these thresholds, then $\hat{b_i} = 0$ is returned.

### 3.1.2 Requirements and Assumptions

1. The model requires a word vectors by a language model that has been pre-trained on a sufficiently large corpus.

2. The model requires *normal* log data, which does not contain anomalies for training.

3. The model is not able to detect anomalies which are only in the variable part of the log messages. The model only considers the templates, i.e. keys.

## 3.2 System Overview

In this section, a broad overview of the overall system is presented, with figure 3.1 illustrating the steps necessary for the learning procedure, followed by anomaly classification. The core concept can be outlined as follows: first, original log sequences are prepared, then a log parser is used to extract templates from the original log sequences and then transform the log sequences to template sequences. Afterwards, the template sequences are transformed into log sequence embeddings by a language representation model. This procedure is described in detail in section 3.3.

For the training part, the log sequence embeddings are fed into a LSTM, which learns to predict the next embedding, which is called the regression task, specified in section 3.4.3 and coloured red in figure 3.1 or the next sequence class, which is called the classification task, specified in 3.4.2 and coloured blue in figure 3.1. The results of these predictions are then compared to the true subsequent log embedding or class of the true subsequent log template, in order to train the model to identify "normal" log data.

The prediction part involves two steps: first, the template sequences obtained from the original log sequences A are altered by changing the order of the sequences or manipulating the templates, as described in section 3.3.5. As a second step, these manipulated sequences are fed to the model which has been trained on embedding sequences not containing any alterations, thereby obtaining the model's predictions if a log line is anomalous or not.

Transfer learning builds onto this process. After a model has been trained as described on dataset A, pre-processing is conducted the same way on a new dataset B, thus obtaining template sequences and embedding sequences. For the classification task, the template sequences of dataset B are mapped to the class mappings of dataset A, and then used for prediction. The regression task functions analogously to learning without transfer. Transfer learning is described in detail in section 3.5

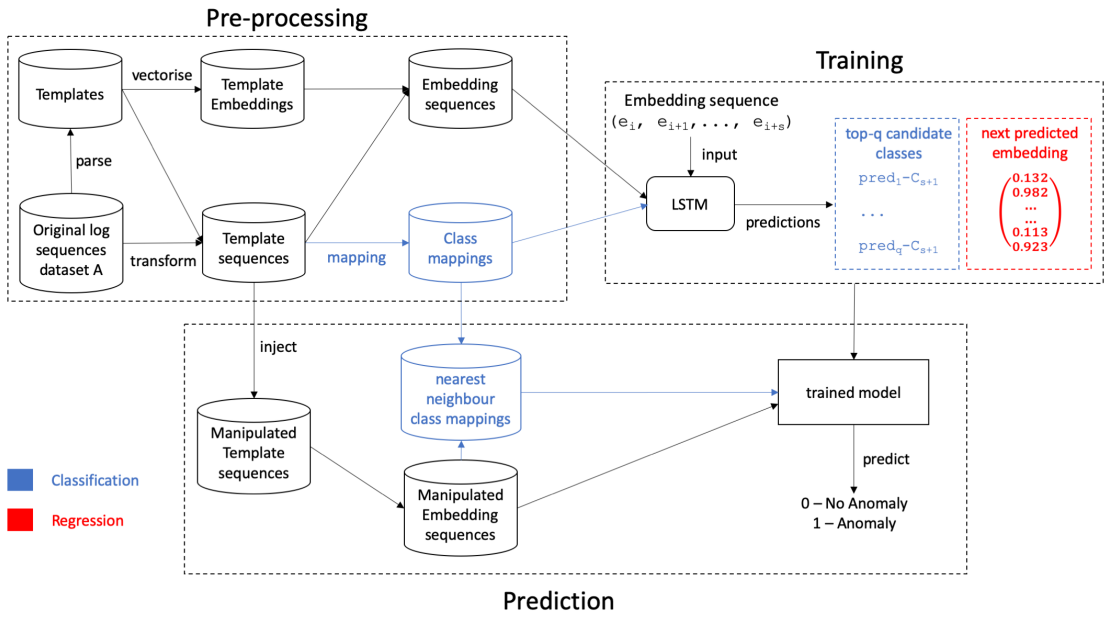



Figure 3.1: Anomaly Detection System

## 3.3 Pre processing

Log files are usually available in an unordered, raw state, and need to be ordered, parsed and transformed into an appropriate format so that they can be handled as sequences

by a LSTM. The required steps for this purpose are outlined in this section. In the first subsection 3.3.1, the steps required for parsing logs are outlined, followed by the transformation into word embedding vectors in 3.3.3.

### 3.3.1 Log Parsing

Log parsing is an important step for automated log analysis, as already described in section 2.5, since raw log messages are unstructured data and contain a lot of extra information. The result of the execution of a log parser can be see in figure 2.9. There are a few important aspects to note here: Not only does the log parsing step extract log templates, it also extracts other valuable information in a structured way, namely timestamps and, in this example the bulk id. Timestamps are needed, in order to make sure that the logs are in the correct chronological order, since it is possible, that system logs are an aggregation of log output of different sub-routines or different instances, which can happen concurrently, thus producing unordered logs. Additionally to sorting by timestamps, it can also be required to sort system logs by group ids, instance ids or bulk ids as in the example figure 2.9 in order to be able to observe each self-contained block separately from other blocks.

### 3.3.2 Template cleansing

Even though log parsing and the aforementioned ordering steps largely improve the further processability of logs for sequential learning, by making it possible to single out the fundamental semantics of a log event, they are still partly made up of special characters and variable names. The following characters are removed:

1. All non-character tokens such as delimiters, digits, and particularly variable placeholders (`<*>`).
2. All concatenations of words are split, for example `sync_power_state` will be split into the separate words `sync`, `power` and `state`
3. All leading, trailing and repeated whitespace characters are removed.

### 3.3.3 Word vectorisation

After the aforementioned pre-processing steps, the log events are transformed into word embeddings, using a language model that is able to convert words or whole sentences into word or sentence embedding, effectively representing function $g$ defined in 3.1.1. Satisfying the following two requirements is essential in the context of providing suited word embeddings for the anomaly detection task:

- Distinguishability: Word embeddings should capture the difference between log events with differing semantics. For example "`<*> Terminating instance`" and "`<*> Deleting instance files <*>`" are log events with highly different semantics, even though they contain equal (instance) and in the broader sense similar (terminating, deleting) words. This means their cosine distance should be high.

- Tolerance: Word embeddings should capture the similarity between different log events with same or very similar semantics. For example, the log event pair "`<*> Creating image`" is changed to "`<*> Image created successfully`" or "`VM up`" is changed to "`VM started`". This in turn should result in a low cosine distance [25].

In order to compare the impact of the choice of a language model, two main approaches are implemented.

#### 3.3.3.1 Transformer-based Language Models

In oder to be able to compare the quality different language model's word embeddings with regards to the task of anomaly detection, it is possible to easily swap the used language model for log event transformation. For this work, the pre-trained language models used for evaluation, are Bert, GPT-2 and XL-Transformers.

### 3.3.4 Finetuning

Word embeddings models are usually provided pre-trained in different formats (e.g. with or without upper case), because training them from scratch is expensive - for Bert, it requires 4 days of training on 16 cloud TPUs for one language [15]. They are trained on large corpuses with unsupervised tasks. In order to make them more useful with regards to the task of anomaly detection, it is reasonable, to adjust the given pre-trained datasets using the log data corpora.

### 3.3.5 Log Alteration

By altering log events, the evolution of log events is being simulated. Since software is changed by developers, also the log statements are subject to constant change. It is desirable to build a flexible model that does not have to be retrained after each update of a log producing software. Log alteration is also used to simulate a different dataset B based on a given dataset A, for applying transfer learning, as outlined in 3.5.

Injection and alteration is done in a programmatically controllable manner. Various types of alterations are injected into original log data, either on the log event itself as in figure 3.2 or on the sequence of log events as in figure 3.3.

Three types of alterations are injected into the log events: a various amount of words is inserted between the tokens, for example words that appear in the context of logs, like "*deleted*", "*during*", "*for*" or "*time*", but for testing purposes, also words that are random in the context . Words can be also deleted. Finally, words can be replaced by new words. All of these alterations can be injected multiple times into the same log event. It is desirable that the system does not detect a log event as an anomaly, that has not been changed much, i.e. only one or two words have been added into a statement (e.g. if "** Took *.* seconds to deallocate network for instance.*" has been changed to "** Took time *.* seconds to deallocate network for this instance.*").

Additionally, it is possible to perform changes on the sequence of logs. In the following example, let $M = (m_i : i = 0, 1, 2, ..., n))$ be a sequence of log events:

- events can be *deleted* from the sequence, meaning that if the event at index $j$ is selected for deletion, the resulting sequence is $M_{del} = (m_0, ..., m_{j-1}, m_{j+1}, m_n)$.
- events can be *shuffled*, meaning that if the event index $j$ is selected for shuffling at index $k$, the resulting sequence is $M_s = (m_0, ..., m_j, m_k, m_{k+1}, ..., m_{j-1}, m_{j+1}, ..., m_n)$
- events can be *duplicated*, meaning that if the event at index $j$ is selected for duplication, the resulting sequence is $M_{dup} = (m_0, ..., m_j, m_j, m_{j+1}, ..., m_n)$
- new events can be *inserted* meaning that if the event $m_{new}$ is inserted at index $j$, the resulting sequence is $M_{ins} = (m_0, ..., m_{new}, m_j, m_{j+1}, ..., m_n)$
- log sequences can be *inverted*, the resulting sequence being $M_{inv} = (m_i : i = n, n-1, ..., 2, 1, 0)$

Just like for the insertion of alterations on the log events themselves, it is desirable of the system not to detect an anomaly for the deletion, duplication or shuffling of events, but for the insertion of anomalies into an event series, and the inversion of log events. These inserted anomaly events can be any type of log events that the system has not seen before.

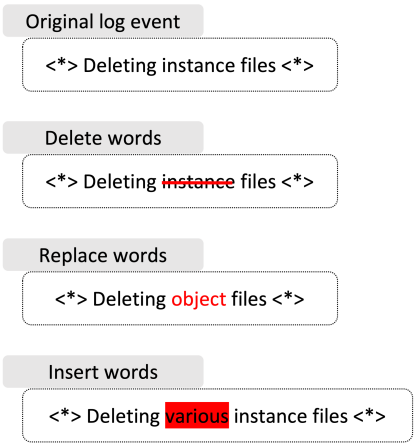



Figure 3.2: Raw log message

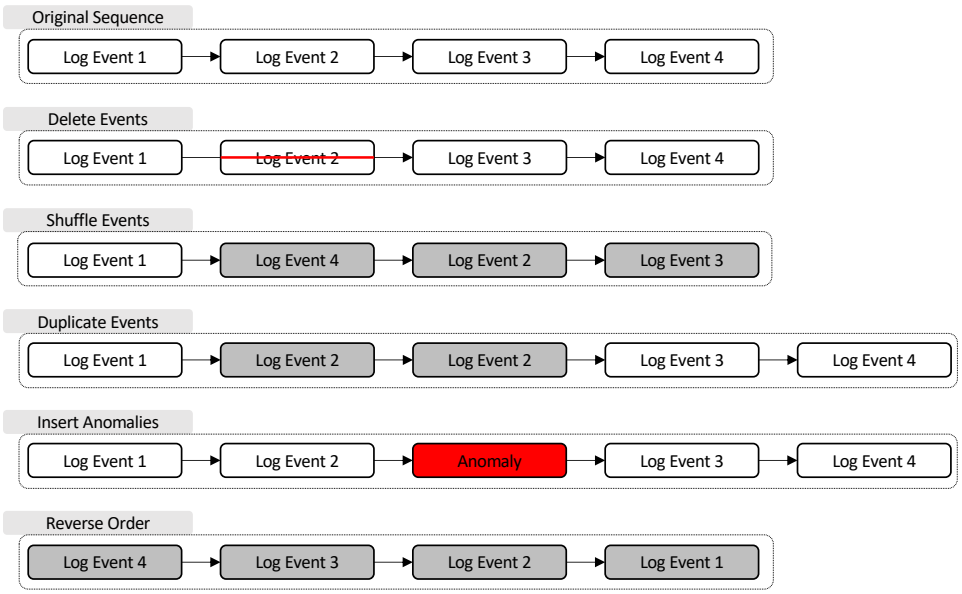



Figure 3.3: Raw log message

## 3.4 Prediction Model

### 3.4.1 LSTM Model

Through the aforementioned steps in 3.3, all log events are transformed into word embeddings $e_i \in \mathbb{R}^w$. In order to learn sequences of logs, $s$ embeddings are concatenated to form an embedding sequence $E$. Taking a sequence of embeddings as input, a *Bi-LSTM* neural network as described in 2.2.2 and 2.2.3 is utilised to predict the class or embedding at position $s + 1$. Figure 3.4 shows the structure of the Bi-LSTM. As a first step, a dropout is applied to the input sequence, which randomly drops out information in order to reduce overfitting and improve generalisation, before feeding it to the forward and backward layers of the Bi-LSTM. Then, the outputs of the Bi-LSTM are again fed into a dropout layer, followed by a fully connected layer, which reduces the output of the LSTM into the desired dimensions, i.e. $\mathbb{R}^w$ for regression and number of classes $c$ for multi-classification. Finally, an activation function $f$ is applied to the last output $o_{s_+1}$, log-softmax for multi-classification and linear for regression, respectively, in order to obtain the model's prediction $p_{s+1}$.

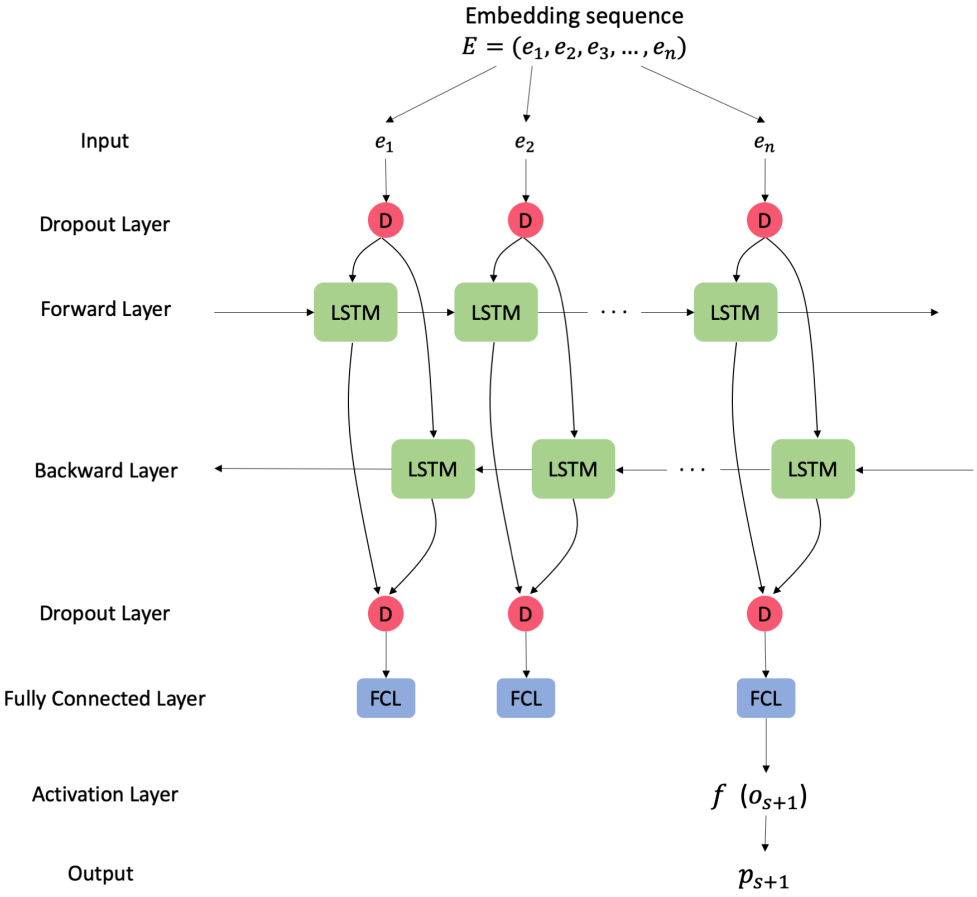



Figure 3.4: Bi-LSTM model

### 3.4.2 Classification

For the multi-classification approach, the finite set of $n$ unique log event templates is mapped to class indices ($c \in \mathbb{N}^+ : c \leq n$). Training of the neural network is then performed on original log data that does not contain anomalies.

- The *input* values of the training data have the dimensions $n$, $s$ and $w$, with $n$ being the number of unique log events, $s$ being the length of the sequence of word embeddings for which the neural network shall learn the consequent class and $w$ being the dimensionality of the log event embeddings.
- The *target* values of the training data are structured as follows: for every subsequence of word embeddings $S_i = (i, ..., i + s)$, there is a corresponding class $c_{s+i+1}$ that stands for the template at position $s + i + 1$. The system is trained to predict that class correctly.

After training has been executed on dataset A, the prediction phase starts, where a dataset B containing anomalies and alterations, as described in 3.3.5, can be processed

by the neural network. For a new incoming dataset B, the system first has to match every template to the template classes of dataset A. For every template in dataset B, the nearest neighbour out of the templates of dataset A is determined and will get the respective class assigned, as depicted in figure 3.5. This means in particular, that for every unique template, the corresponding word embedding is retrieved, and then every one of the word embeddings of dataset B is mapped to the word embedding from dataset A with the lowest cosine distance. Additionally, a threshold has to be found, so that if for a given word embedding in dataset B, no corresponding word embedding with a cosine distance below this threshold is found, that template shall not get a class assigned, this would otherwise lead to a situation where the log event *"System restarted"* gets mapped to any of dataset A's template classes, which is not desirable behaviour.

After the matching process is finished, the system can read in the sequences of log events of dataset B. For every sequence of log events $S_i$ of length $s$, the system returns a probability distribution $Pr[c_{s+i+1}|S_i] = \{c_1 : p_1, c_2 : p_2, ..., c_n : p_n\}$ that denotes the probability of each log template class to appear as the consequent one. It is possible, that there are multiple candidates for the following template. For example, if the system is attempting to terminate an instance, then the corresponding template to class $c_{s+i+1}$ could be either '*Instance terminated successfully*' or '*Waiting for instance to terminate*'. The possible template classes $c_i$ are sorted based on their probabilities. A predicted template class is considered normal, if it is among the top $g$ candidates. It is marked as anomalous otherwise.

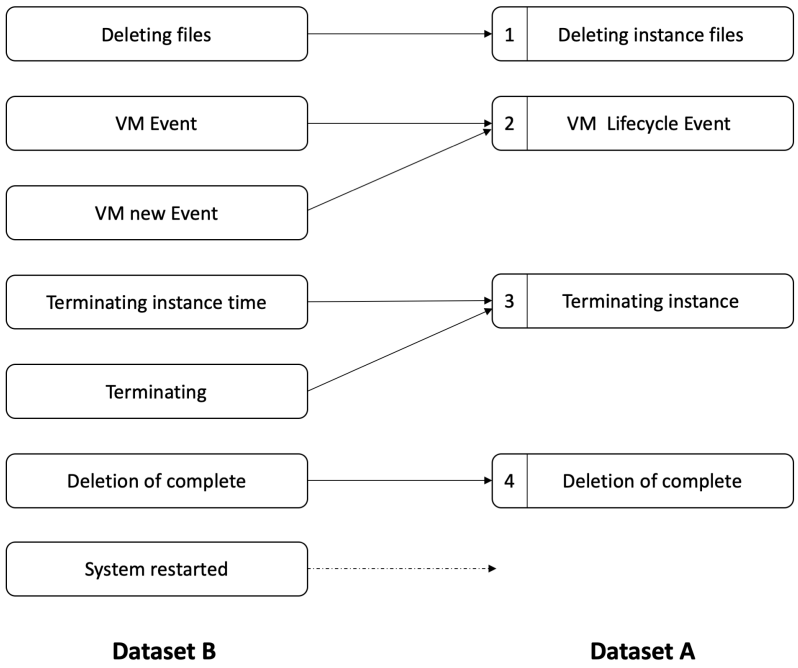



Figure 3.5: Template mapping

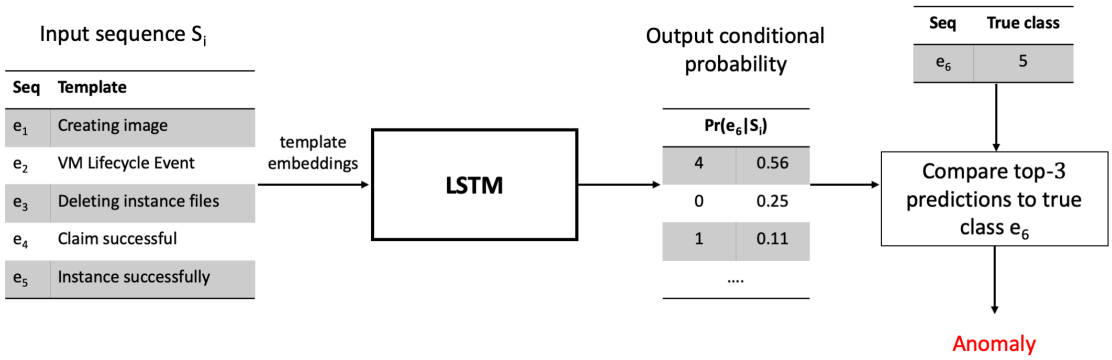



Figure 3.6: Class Prediction example for $g = 3$

### 3.4.3 Regression

For the regression approach, the neural network is trained to solve a regression task, with the input values of the training data being structured as described in 3.4.2, while the corresponding target value for the sequence of embeddings $(i, ..., i+s)$ is the embedding of the log event at position $i+s+1$, meaning the neural network shall predict the next embedding. After training on the original dataset, the mean squared error loss of every target word vector at position $i+s+1$ of the corresponding input sequence $(i, ..., i+s)$, and the predicted word vector of the neural network, is computed. Afterwards, the *q-th* percentile of the agglomerated loss values is computed (the optimal value $q$ for the following purpose is to be determined by a simple grid-search). Now, for the sequences of the manipulated dataset, the loss values are computed the same way as for the original dataset. The system will then mark every log event whose word embedding's loss value is above the calculated percentile as an anomaly (1), otherwise as non anomalous (0).

## 3.5 Transfer Learning

Transfer learning is the main focus of this work. It builds upon the aforementioned techniques and uses them to develop an infrastructure-agnostic anomaly detection model. With the help of these techniques, frequent re-training of models can be avoided and models trained on one dataset can be ported to be used with different datasets. The way transfer learning is executed differs from the classification approach, which is further outlined in 3.5.1 and the regression approach, explained in 3.5.2.

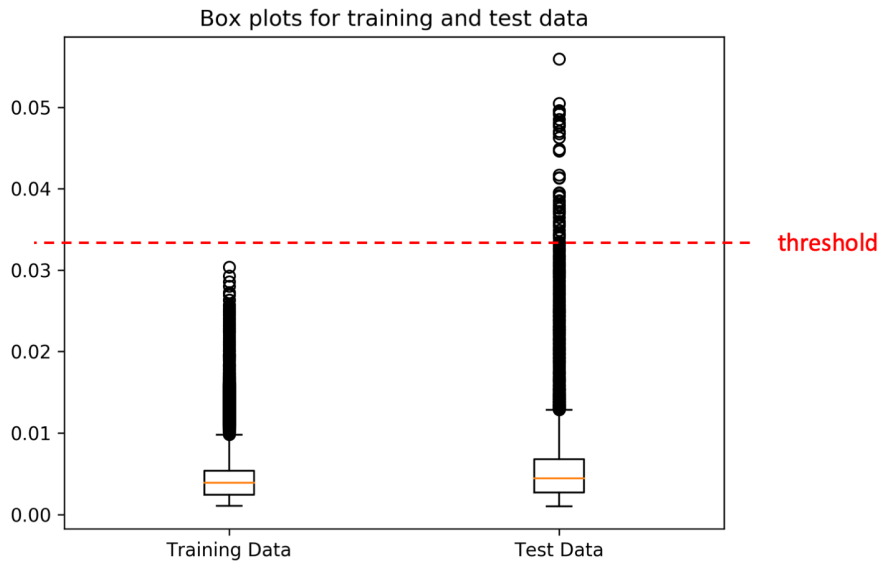



Figure 3.7

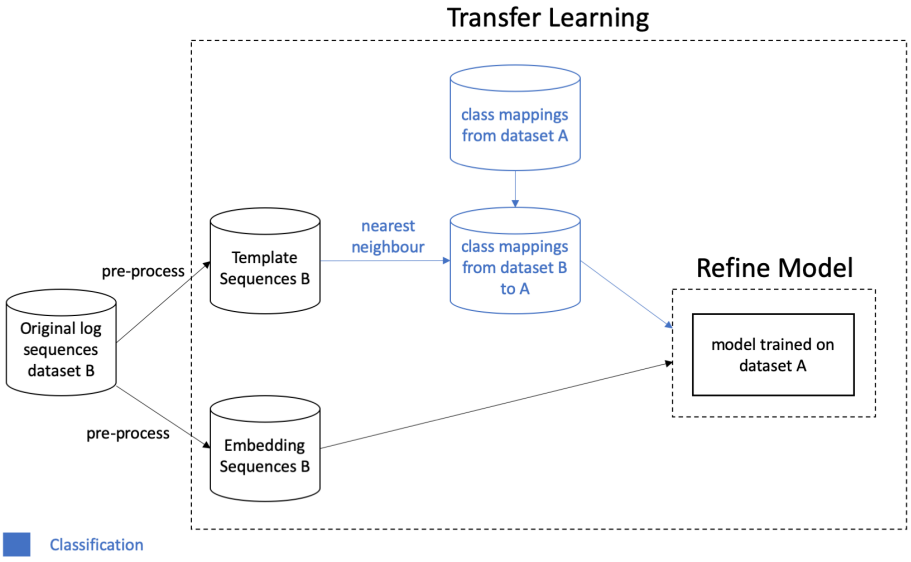



Figure 3.8: Transfer Learning System

### 3.5.1 Classification

Since training on dataset A has been conducted using classification, a mechanism for mapping the templates of dataset B to the classes which have been assigned to the templates of dataset A. For this, for every template of dataset B, the nearest neighbour of dataset A is assigned, as described in 3.4.2 and depicted in figure 3.5, without using a threshold for matching nearest neighbours, so that every template of dataset B will get a template class from dataset A assigned. The

### 3.5.2 Regression

For transfer learning using the regression-based approach, no further adaptations are required - the model is trained on a given dataset A, followed by few-shot training on dataset B. The model is then ready to make predictions on anomalies in dataset B using the approach described in 3.4.3

## 3.6 Possible Improvements and Extendibility

In this section, possible improvements to the model are identified. Possible improvements include the way word embeddings are obtained from language models and

The word embeddings are taken from the used language models as they are. Finetuning on the log corpora is only conducted using the default tasks that have been used to train the language model on extremely large corpora. The corpora on log data are likely to be too small. Even though most log events are sentences in English, they are of a very ting A deeper investigation on how to train the language model specifically on the task of anomaly detection could potentionally be useful in order to obtain better results.

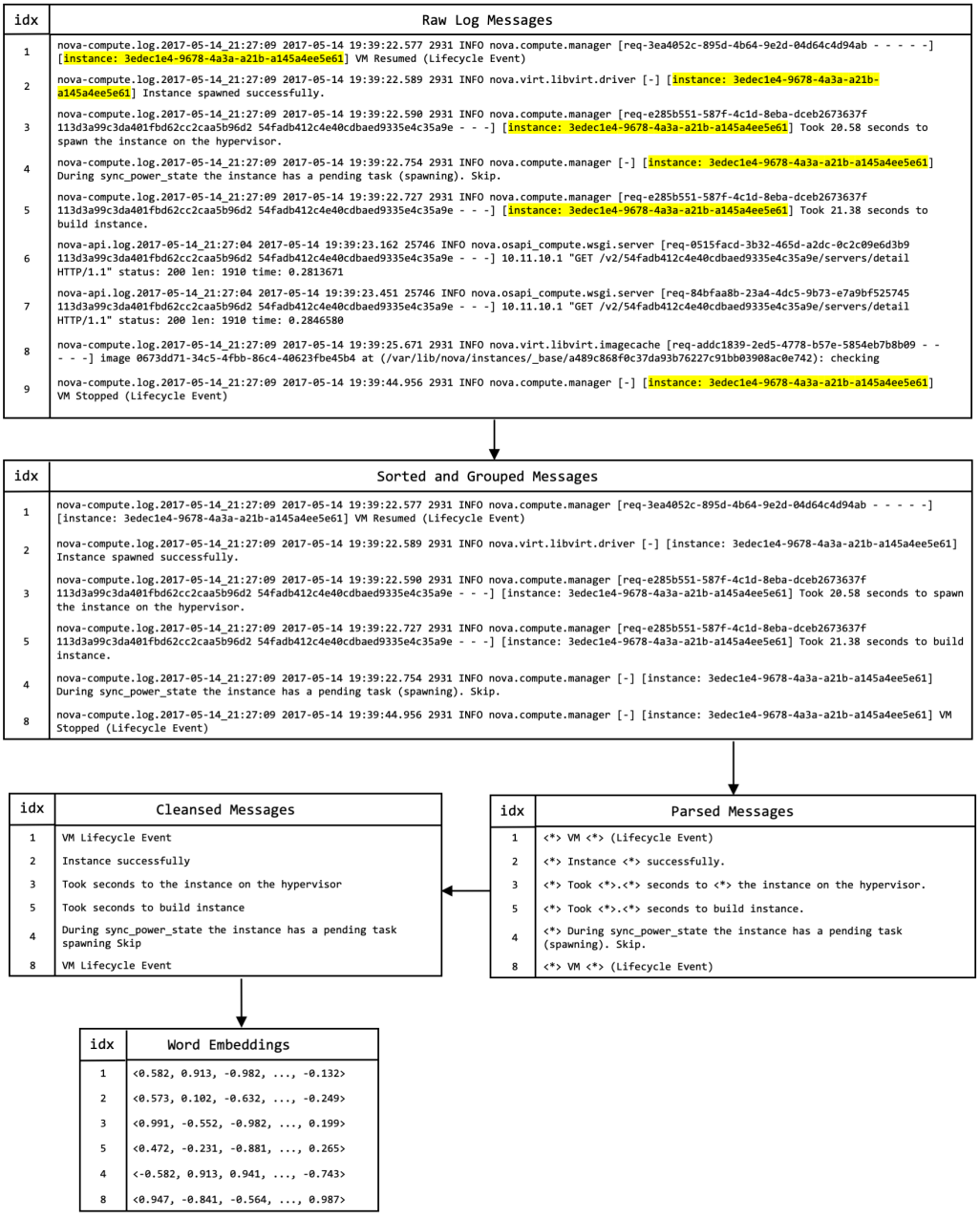



Figure 3.9: One full iteration of pre-processing

# 4 Results

In the following chapter, the achieved results of the concept are presented. The described approaches are evaluated with regards to the common metrics precision, recall, and F1-Score. Different hyperparameter setups are being discussed and are visualised in graphs. In particular, the language models Bert, XL-Transformers and GPT-2 as described in 3.3.3.1 are compared, showing, which vectorisation method yields the best results. Additionally, the regression-based method as described in 3.4.3 and the multi-classification method as described in 3.4.2 are compared, showing advantages or disadvantages among each other.

## 4.1 Experimental Setup

### 4.1.1 Anomaly Detection on one Dataset

For evaluating the model, the OpenStack datasets "normal log dataset 2" containing 137k log lines and the "log dataset having performance anomalies" containing 18k log lines, provided by the DeepLog authors at the University of Utah are used [26]. Since their log dataset having performance anomalies contains anomalies which are only detectable by inspecting the timestamps and parameters of the log events, as described in 2.9, i.e. the variable part of the log event which is not visible in the template after parsing, anomalies are injected into the dataset. In order to assess the quality of the used word embeddings, log alterations, as described in 3.3.5 are additionally injected into the dataset containing anomalies, in order to simulate the instability of logs which can arise from

### 4.1.2 Transfer Learning

In order to examine the ability of the model to transfer the knowledge obtained from one dataset to a different one, the same OpenStack log dataset as utilised in 4.1.1 is used as a basis. Then, in order to simulate a different dataset, various of the alterations discussed in 3.3.5 are injected all at once. For the following experiments, line shuffling, duplication and deletion, and word insertion, removal and replacement are injected into the dataset at various ratios.

## 4.2 Evaluation

### 4.2.1 String cleansing

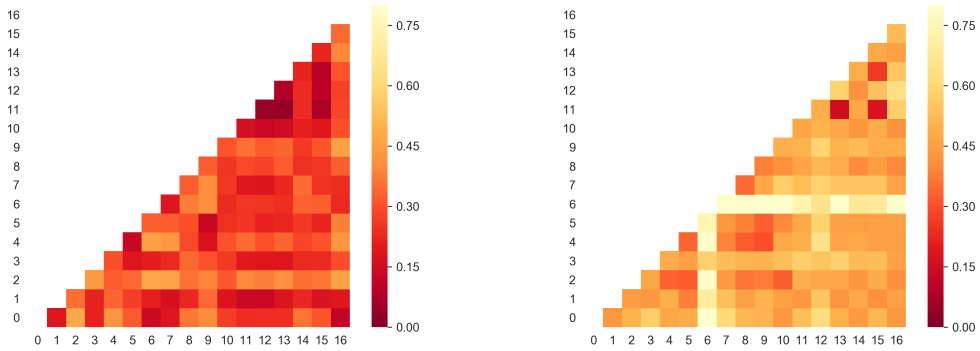
String cleansing, as described in 3.3.2, can potentially improve distinguishability between templates drastically in the used dataset. For Bert, the pairwise cosine distances before cleansing are depicted in figure 4.1a, after cleansing in figure 4.1b. The corresponding templates to the indices on the x and y axes before and after cleansing can be found in table 4.2 and table 4.3 respectively. The cosine distances before and after cleansing for GPT-2 can be found in figure 4.2a and figure 4.2b, and for XL-Transformer in figure 4.3a and figure 4.3b, respectively. The average pairwise cosine distances between templates before and after cleansing can be seen in table 4.1. Note that the cosine distances between templates appear to be relatively low for GPT-2 before and after cleansing. Even though cleansing results in a two-fold increase in the distances, the initial value is already very low. We can see how the distinguishability between templates increases for Bert and even more impressively for XL-Transformers. While Bert has a slightly higher average pairwise cosine distance before cleansing, XL-Transformers highly benefits from cleansing with an average value of 0.62. This underlines the importance of this step in order to meet the requirements postulated in 3.3.3, depending on the deployed language models.

| Model | Before cleansing | After cleansing |
|---|---|---|
| XL | 0.2232 | 0.6223 |
| Bert | 0.2416 | 0.4449 |
| GPT-2 | 0.0024 | 0.0047 |

Table 4.1: Average pairwise template cosine distances.

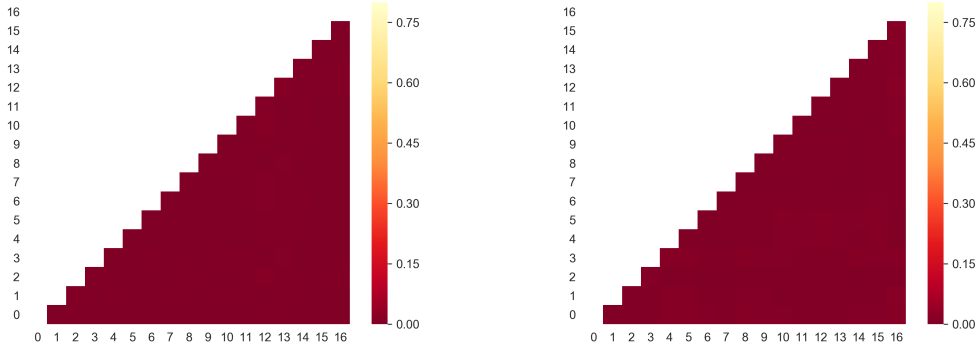
### 4.2.2 Finetuning

As described in 3.3.4, finetuning can potentially help to produce word embeddings that are more adequate for solving a certain task, it is thus desirable to produce word embeddings that help solving the task of anomaly detection better. As described in 3.3.3, a high cosine distance between semantically different templates is required. The dataset that consists of the templates in table 4.3 has been chosen for finetuning. Since the pre-trained language models at hand (namely *bert-base-uncased* and *gpt2*) have been trained on a large corpus, finetuning would also need to be executed on a sufficiently large corpus. Since this is not the case, the results of finetuning for a maximum of four epochs, as suggested by the Bert authors [14], does not yield the desired results. As it can be seen in figure 4.5, it was not possible to increase the cosine distances between templates on the task of Masked LM (as described in 2.4.2), compared to the cosine distances depicted in figure **??**. The average distance between templates dropped to 0.3016 from 0.4449. The fact that the loss on the evaluation part of the dataset is not



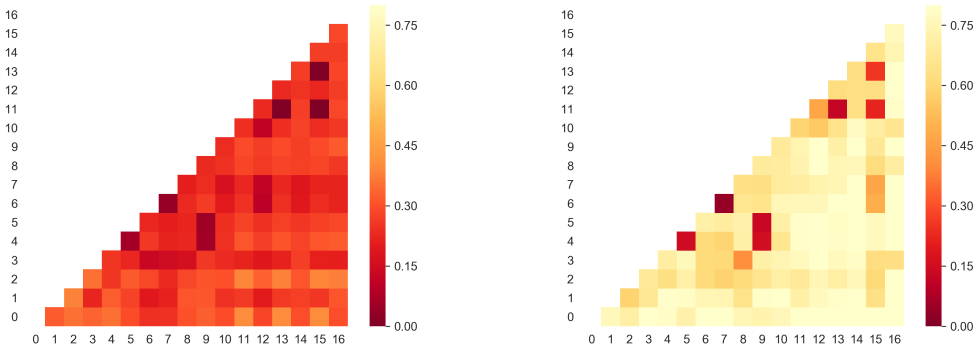

(a) Before cleansing. (b) After cleansing.

Figure 4.1: Bert pairwise template cosine distance.




(a) Before cleansing. (b) After cleansing.

Figure 4.2: GPT-2 pairwise template cosine distance.



(a) Before cleansing. (b) After cleansing.

Figure 4.3: XL-Transformers pairwise template cosine distance.

decreasing adequately, as shown in figure 4.4, shows that training on such a small corpus is not able to generalise well enough, which makes finetuning on the default learning task not useful in this case. Since the Huggingface Transformers library does not offer out of the box finetuning interfaces for GPT-2 and XL-Transformers on the same task as for Bert, they are not further investigated for finetuning.

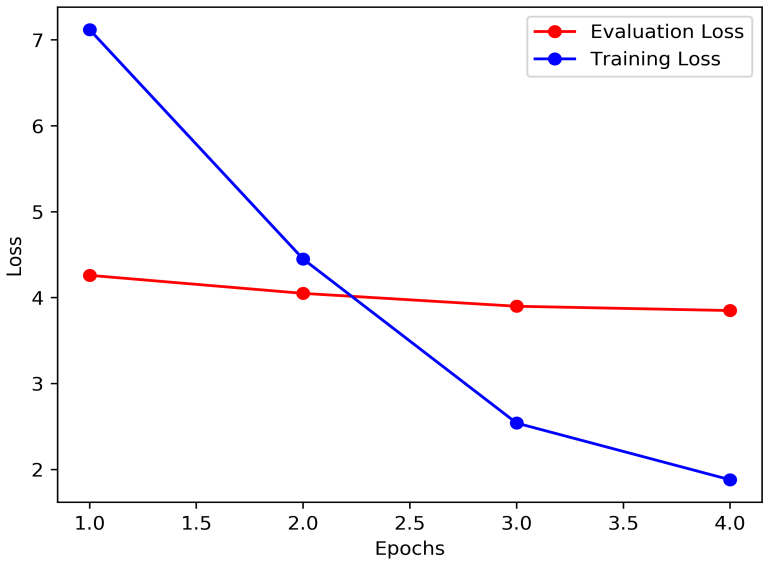



Figure 4.4: Training and evaluation loss for finetuning on masked LM.

| Index | Template |
|---|---|
| 0 | ⟨∗⟩ Creating image |
| 1 | ⟨∗⟩ VM ⟨∗⟩ (Lifecycle Event) |
| 2 | ⟨∗⟩ During sync_power_state the instance has a pending task (spawning). Skip. |
| 3 | ⟨∗⟩ Instance ⟨∗⟩ successfully. |
| 4 | ⟨∗⟩ Took ⟨∗⟩.⟨∗⟩ seconds to ⟨∗⟩ the instance on the hypervisor. |
| 5 | ⟨∗⟩ Took ⟨∗⟩.⟨∗⟩ seconds to build instance. |
| 6 | ⟨∗⟩ Terminating instance |
| 7 | ⟨∗⟩ Deleting instance files ⟨∗⟩ |
| 8 | ⟨∗⟩ Deletion of ⟨∗⟩ complete |
| 9 | ⟨∗⟩ Took ⟨∗⟩.⟨∗⟩ seconds to deallocate network for instance. |
| 10 | ⟨∗⟩ Attempting claim: memory ⟨∗⟩ MB, disk ⟨∗⟩ GB, vcpus ⟨∗⟩ CPU |
| 11 | ⟨∗⟩ Total memory: ⟨∗⟩ MB, used: ⟨∗⟩.⟨∗⟩ MB |
| 12 | ⟨∗⟩ memory limit: ⟨∗⟩.⟨∗⟩ MB, free: ⟨∗⟩.⟨∗⟩ MB |
| 13 | ⟨∗⟩ Total disk: ⟨∗⟩ GB, used: ⟨∗⟩.⟨∗⟩ GB |
| 14 | ⟨∗⟩ ⟨∗⟩ limit not specified, defaulting to unlimited |
| 15 | ⟨∗⟩ Total vcpu: ⟨∗⟩ VCPU, used: ⟨∗⟩.⟨∗⟩ VCPU |
| 16 | ⟨∗⟩ Claim successful |

Table 4.2: Templates before cleansing

### 4.2.3 Classification

### 4.2.4 Regression

## 4.3 Discussion of Results

| Index | Template |
|---|---|
| 0 | Creating image |
| 1 | VM Lifecycle Event |
| 2 | During sync power state the instance has a pending task spawning Skip |
| 3 | Instance successfully |
| 4 | Took seconds to the instance on the hypervisor |
| 5 | Took seconds to build instance |
| 6 | Terminating instance |
| 7 | Deleting instance files |
| 8 | Deletion of complete |
| 9 | Took seconds to deallocate network for instance |
| 10 | Attempting claim memory MB disk GB vcpus CPU |
| 11 | Total memory MB used MB |
| 12 | memory limit MB free MB |
| 13 | Total disk GB used GB |
| 14 | limit not specified defaulting to unlimited |
| 15 | Total vcpu VCPU used VCPU |
| 16 | Claim successful |

Table 4.3: Templates after cleansing

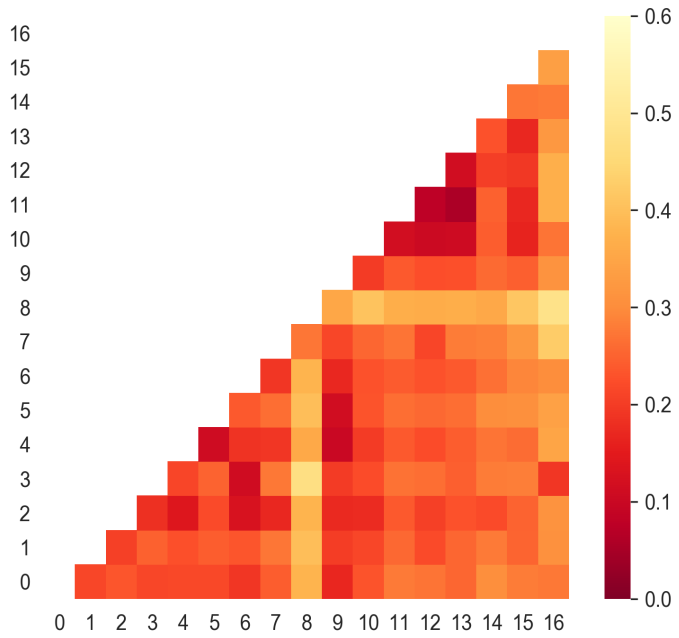



Figure 4.5: Cosine distance between templates after cleansing and finetuning

# 5 Related Work

## 5.1 Sequence-Based Anomaly Detection in Logs

### 5.1.1 DeepLog: Anomaly Detection and Diagnosis from System Logs through Deep Learning

Du et al. proposed DeepLog [2], a prominent example of a model that treats system logs as natural language sequences. An overview of the model is depicted in figure 5.1. The first step of the proposed model is like in most of the works in the area: Logs are first pre-processed with a log parser, they separate the constant from the variable part. Log templates are mapped to log keys $k_i$, which are just indices between 0 to the number of different templates. For each log entry $e_i$, the elapsed time between $e_i$ and $e_{i-1}$ are stored in $\vec{v}_{e_i}$, together with parameter values in a parameter value vector. An LSTM is then trained on the sequences $k_i$ to learn normal system execution paths. Given a window size of $h = 3$, a sequence of log keys $\{k_5, k_{11}, k_2, k_{14}, k_{15}\}$ would results in the *input sequence* and *output sequence* for training of $\{k_5, k_{11}, k_2 \rightarrow k_{14}\}$ and $\{k_{11}, k_2, k_{14} \rightarrow k_{15}\}$. Given these sequences of keys, the system is trained to maximise the probability of having $k_i \in K$ as the next log key value, thus learning the probability distribution $Pr(m_t = k_i | m_{t-h}, ..., m_{t-1})$, so given a log key sequence of length $h$, outputs a probability distribution of all possible log key values. A log key value is treated as normal, if it's among the top $g$ candidates. For the detection stage, new log key entries $e_t$ are parsed into a log key $m_t$ and parameter value vector. Then, the trained model is used, to check if the incoming log key is normal, by sending $w = \{m_{t-h}, ..., m_{t-1}\}$ as input. Additionally, the parameter value vector is checked. If the log entry is labeled being abnormal, the model provides semantic information for users to manually diagnose the anomaly. In order to adapt to changing patterns and log entries, the user has the possibility to mark a detected anomaly as a false positive, thus updating the model.

For verification of the model, the authors deployed an OpenStack experiment to fabricate their own log data. They produce over 1 million log entries, with 7% being abnormal. The model is able to achieve a precision of 0.96, recall of 1.0 and F1-score of 0.98.

Even though the model can be adjusted after the training phase on a particular dataset is already completed, by manually reporting false positives, thus enabling the system to adapt to changing or new sequences of logs, it is not able to dynamically adapt to changes on the log events themselves. If log data changes on the log event level, re-training of the model is necessary.

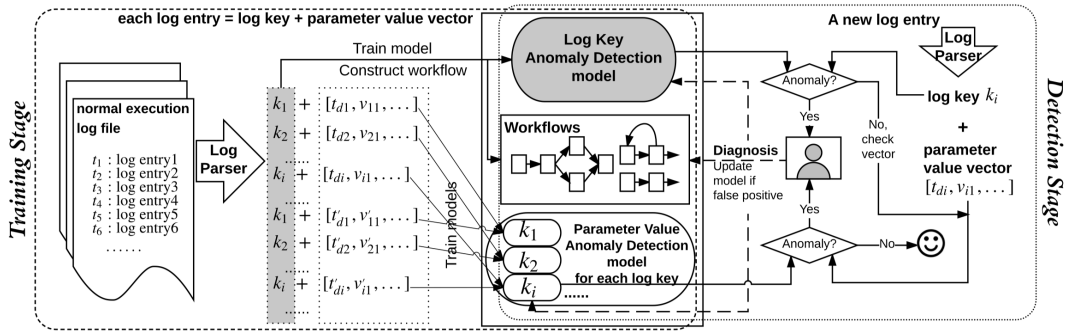



Figure 5.1: DeepLog model overview [6]

### 5.1.2 LogAnomaly: Unsupervised Detection of Sequential and Quantitative Anomalies in Unstructured Logs

*LogAnomaly*, the approach proposed by Meng et al. [1] models a log stream as a natural language sequence. Log event sequences are first parsed into template sequences using FT-Tree. These sequences are then transformed into embedding sequences using a novel word representation method, template2Vec, which is inspired by word2Vec [27]. Figure 5.4 shows the steps included for template2Vec in the offline learning stage: (1) shows the inclusion of common synonyms and antonyms in the English language extracted from WordNet [28]. Additionally, log-data-specific synonyms and antonyms can be added. In the second (2) step, dLCE [29] is used as an embedding model, to generate word vectors that represent the words in templates, which are then transformed (3) into template vectors [1].

After log the sequences of log events $S = (s_1, s_2, ..., s_m)$ have been transformed into template vector sequences $V = (v_{s_1}, v_{s_2}, ..., v_{s_m})$, they apply an Attention-based Bi-LSTM to learn sequences of normal logs. The sequence for detection is a sliding window of the $w$ most recent template vectors, meaning that for a template vector sequence $V_j = v_{(s_j)}, v_{(s_{j+1})}, ..., v_{(s_{j+w-1})}$, the LSTM learns to predict the template vector $v_{j+w}$. Additionally to sequential patterns, LogAnomaly considers quantitative patterns in sequences of templates. For example, opening files should also be closed, so the number of logs indicating that a file was opened should be equal to the number of logs indicating that a file was closed. If a log would break a certain invariant, it can be assumed that an anomaly has occurred during execution. For log messages $s_i \in S_j$, with $S_j$ being a subsequence of $S$, the count vector of the log sequence $s_{i-w+1}, s_{i-w+2}, ..., s_i$ is calculated, denoted as $C_i = (c_i(v_1), c_i(v_2), ..., c_i(v_n))$, with $c_i(v_k)$ being the number of occurrences of $v_k$ in the template vector sequence $v_{i-w+1}, s_{i-w+2}, ..., v_i$. $C_j$, $C_{j+1}, ..., C_{j+w-1}$ are then inputs for the LSTM. This process is laid out in figure 5.2 [1].

In order to deal with new log templates in an online fashion, if an arriving log cannot be matches to an existing template, FT-Tree is utilised to extract a template from the new log and its template vector is calculated. Subsequently, the template will be matched on an existing one, based on the similarity among template vectors [1].

For verification of the model, the authors employ a manually labeled BGL dataset containing around 4.7 million logs, and a HDFS dataset with around 11 million logs, both with manual labels on anomalous logs or blocks of logs. For the BGL dataset they achieve a precision of 0.97, recall of 0.94 and F1-score of 0.96. For the HDFS dataset, they achieve a precision of 0.96, recall of 0.94 and F1-score of 0.95 [1].

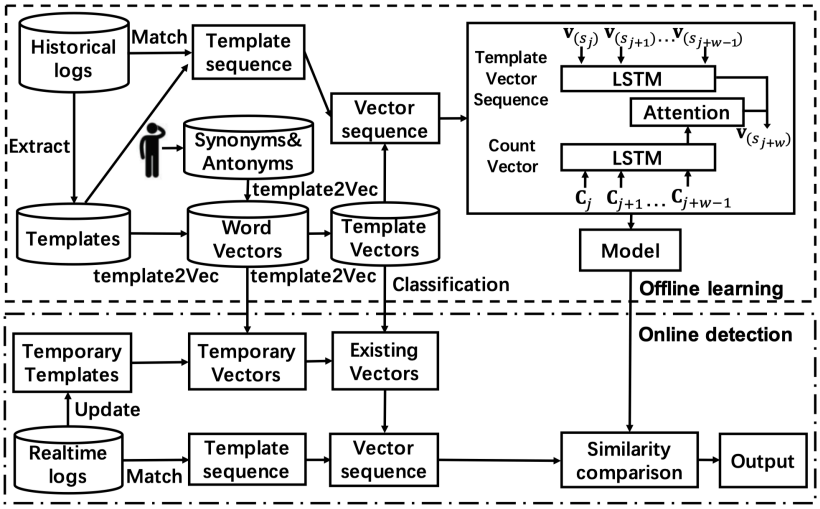



Figure 5.2: LogAnomaly model overview [1].

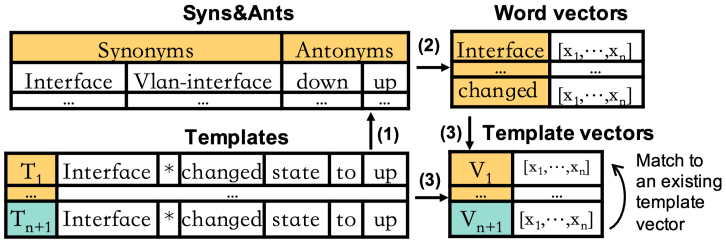



Figure 5.3: Example of Template2vec [1].

### 5.1.3 Robust Log-Based Anomaly Detection on Unstable Log Data

Zhang et al. proposed *LogRobust* [25], emphasising the necessity of anomaly detection on log data being sufficiently robust to the unstable nature of log data which is twofold: They are *evolving*, meaning that frequently modifying source code naturally leads to logging statements getting altered. Also during collection, retrieval and pre-processing of log data, *processing noise* is introduced into the original log data. For example, in large-scale systems, many logs are produced by separate distributed components, potentially leading to missing, duplicated or disordered logs due to network errors or limited system throughput.

In order to capture the semantics of log events, LogRobust treats sequences of log events like sequences of natural language sentences, exactly like in 5.1.2. After adopting Drain to parse log data and extract log templates from it, they apply FastText [30] in order to replace words with corresponding vectors with dimension $d = 300$, thus transforming a log-event sentence $S$ into a word vector list $L = (v_1, v_2, ..., v_N)$, where $v_i \in \mathbb{R}^d$ and $N$ being the number of tokens in a log-event sentence. Next, all $N$ word vectors that represent a log event are aggregated into a fixed-dimension vector. For this purpose, TF-IDF is applied to measure the importance of words in sentences. For example, if a word appears frequently in a log event, it means that this word is potentially highly representative for this log event, thus increasing its *Term Frequency* (TF) value. On the contrary, if a word appears in many log events, it diminishes the distinguishability of log events, leading to a low *Inverse Document Frequency* (IDF) value. Then, for each word, its TF-IDF weight is calculated by TF $\cdot$ IDF. Finally, the template vector $V \in \mathbb{R}^d$ is obtained by summing up the weighted word vectors.

The log sequences are then split into subsequences and then used as input for an Attention-based Bi-LSTM. Hidden states at time step $t$ of the forward ($f$) and backward ($b$) pass are concatenated as $h_t = \text{concat}(h_t^f, h_t^b)$. Log data noise can be reduced with the help of the attention layer, which can automatically learn the importance $\alpha_t$ of a log event, which can be computed by using the weight $W_t^\alpha$ of the attention layer at time step $t$ as follows: $\alpha_t = \tanh(W_t^\alpha \cdot h_t)$. The sum of all hidden states produces the prediction output: $pred = \text{softmax}\ (W \cdot (\sum_{t=0}^{t=T} \alpha_t \cdot h_t))$.

For evaluation, the authors use a HDFS dataset [31] which contains around 24 million log messages with about 2.9% labelled anomalies, commonly used for benchmarking. They simulate processing noise by applying various small changes to the order of log sequences (unstable seq.) and the evolution of log events by randomly removing or adding words from log events (unstable event). The resulting datasets can be seen in 5.1. For an injection ratio of 5% on *NewTesting1*, LogRobust has a precision of 1.00, recall of 0.91 and an F1-Score of 0.95. Increasing the injection ratio in 5% steps decreases the F1-Score by roughly 2 percentage points, while the baseline methods degrade more. The results are similar on *NewTesting2*. On the unmodified HDFS dataset, precision is 0.98, recall 1.00 and F1-Score 0.99.

| Set | Unstable event | Unstable seq. | Normal | Anomaly | Total |
|---|---|---|---|---|---|
| Training | No | No | 6,000 | 6,000 | 12,000 |
| NewTesting1 | Yes | No | 50,000 | 1,000 | 51,000 |
| NewTesting2 | No | Yes | 50,000 | 1,000 | 51,000 |

Table 5.1: Manipulated HDFS dataset

There has been a large amount of research and development of new approaches for anomaly detection in logs. Approaches can be characterised by the following categories: supervised learning models, unsupervised learning models, statistical models, classical machine learning models and finally deep learning models. Numerous supervised learning

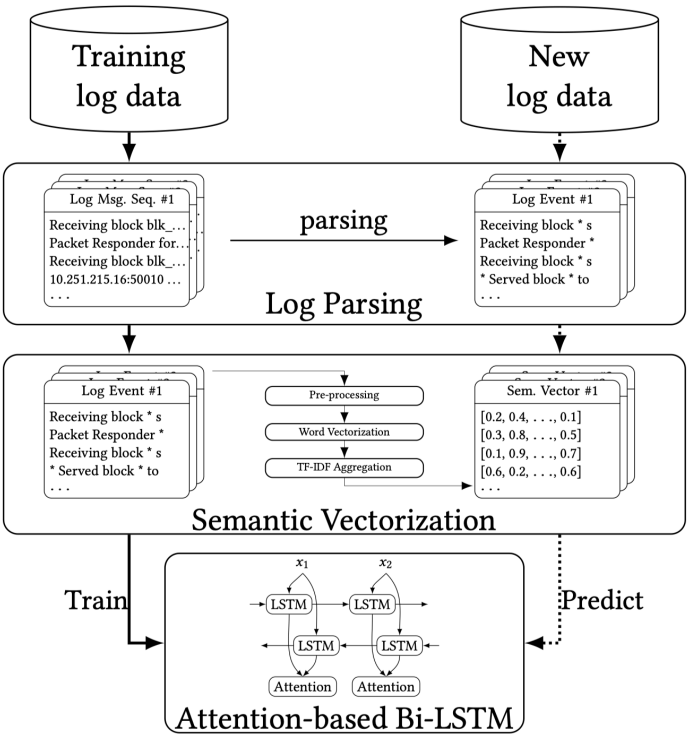



Figure 5.4: Overview of LogRobust [25].

methods were applied to solve the problem of log anomaly detection. Liang et al. [32] and Yuan et al. [33] trained a SVM classifier to detect errors. Farshchi et al. [34] adopt a regression-based method to find correlations between an operation's logs and the operation activity's effect on cloud resources. Chen et al [35] presented a decision tree learning approach to diagnose failures in large Internet sites. However, these methods have two limitations: they rely on system-specific labeled log data for training and do not provide a general method to cope with ever-changing log data.

Additionally, unsupervised learning methods have been proposed. Xu et al. [31] use the Principal Component Analysis method to construct a log count matrix, grouping log events to sessions with the session id which is available for every log event. Lin et al [36] and [37] both propose approaches that cluster logs.

The recent remarkable advances of deep learning depict new promising paths for anomaly detection in logs. While LSTMs have been put to use in detecting anomalies in time series generally [38], they have been used in anomaly detection in logs: Du et al. [2] present DeepLog: first, log events are mapped to keys, the sequential order of these keys is learned using a LSTM to detect anomalies. Zhang et al. [39] use a LSTM similarly. Even though these approaches yield good results, they are not able to cope with changing log data, since log events have to be transformed into fixed indices.

There are studies that have applied NLP techniques and consider log events as natural

language. Bertero et al [40] used Google's word2vec algorithm to obtain word embeddings, exploiting the obtained feature space using standard classifiers, like SVM and Random Forest, to detect anomalies. Zhang et al. [39] additionally to using the LSTM model for time series prediction, apply TF-IDF weight and consider each log event as a word. Brown et al. [41] use combine attention based models together with word word embeddings. These approaches do not take into account the contextual information in log sequences.

Recently, LogRobust and LogAnomaly use pre-trained word embeddings, using an attention-based Bi-LSTM model to learn log sequences.

# 6 Conclusion

The final chapter summarizes the thesis. The first subsection outlines the main ideas behind Component X and recapitulates the work steps. Issues that remained unsolved are then described. Finally the potential of the proposed solution and future work is surveyed in an outlook.

## 6.1 Summary

Explain what you did during the last 6 month on 1 or 2 pages!

The work done can be summarized into the following work steps

- Analysis of available technologies
- Selection of 3 relevant services for implementation
- Design and implementation of X on Windows
- Design and implementation of X on mobile devices
- Documentation based on X
- Evaluation of the proposed solution

## 6.2 Dissemination

Who uses your component or who will use it? Industry projects, EU projects, open source...? Is it integrated into a larger environment? Did you publish any papers?

## 6.3 Problems Encountered

Summarize the main problems. How did you solve them? Why didn't you solve them?

## 6.4 Outlook

Future work will enhance Component X with new services and features that can be used ...

# List of Acronyms

| | |
|---|---|
| 3GPP | 3rd Generation Partnership Project |
| AJAX | Asynchronous JavaScript and XML |

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# Annex