# Deep-Learning Based Anomaly Classification in Unstructured Log Data

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## Abstract

Anomaly detection and type classification problem for time series is a tedious but mush beneficial task, especially harnessing the massive amount of data generated by variable systems to create value for technology development and business strategies. By using the state-of-art machine learning techniques and deep neural networks, we propose a series of approaches to assist in focusing on detecting the most crucial types of anomalies and gaining critically insights of log information. Here we propose a state-of-the-art recurrent neural network approach and measure the accuracy of our diverse array of classification algorithms. The results reveal the strengths and advantages of our long short-term memory neural network and convolutional neural network for real-world classification tasks of anomaly types.

**Index Terms**—Anomaly Classification, Machine Learning, Deep Learning, Log Analysis, Long short term memory, Recurrent neural network, Convolutional neural network

## 1 Introduction

During the last decade, a plenty of system serves have become highly popular, and it also induces new challenges that impact operators. The management of system log data and outliers potentially affecting the end users. … For a complex scenario like this, it is of vital importance to effectively detect and classify the occurrence of system anomalies for reducing the loss of the profit.

We propose a simple yet efficient approach to detect and classify system operation anomalies using machine learning and deep learning techniques. Deep learning algorithms build data-driven models from labeled data and make predictions on data which they can learn from. Deep learning provide a more promising alternate for detecting and categorizing log anomalies based on the large set of original features or more relevant set of features for classification process. Deep learning has been largely used in the field of image classification, speech recognition, etc., but not much in log anomalies. Our studies have shown that deep learning algorithms are able to achieve potentially high classification accuracy.

To obtain favorable performances of anomaly classification, we propose a deep learning model based on well-known long short term memory (LSTM) recurrent neural network and deep convolutional neural network. A LSTM recurrent neural network is a classification algorithm that classifies instances by … Deep learning algorithms are like appealing black-box solutions, it’s efficient but very challenging to understand the detailed reasons leading to a particular classification result. In addition, LSTM explicitly show …, the learning algorithm automatically select the most discriminating features. CNN…. Last but not least, previous work [] has shown that deep learning outperforms other machine learning algorithms for the sake of log anomaly classification.

The remainder of this article is organized as follows: Section 2 briefly reviews the related works. Section 3 reveals our deep learning approaches utilized in the rest of the paper. Section 4 describes the proposed anomaly classification experiments including the generation of the semantic datasets used for models training and evaluation purposes. Section 5 presents the discussions of the obtained anomaly classification results. Finally, the last section concludes out work.

Usually, log data is analyzed in order to detect misuses of a system or suspicious events indicating anomalies.

Anomaly discrimination related problems are addressed in a great deal of practical applications, including fraud detection, intrusion detection, system health monitoring as well as event detection in sensor networks. Anomalous items are also referred to as outliers, novelties, noise, deviations and exceptions [1].

In contrast to typical unsupervised anomaly detection, which is often applied on unlabeled data set under the assumption that the majority of the instances are normal, instead, we here take a data set that has been labeled as normal and abnormal into account for supervised anomaly classification tasks with the state-of-the-art deep learning algorithm classifier. In supervised learning, removing the anomalous data from the data set often results in a statistically significant increase in accuracy [2].

There are a diverse array of anomaly detection techniques have been proposed, such as density-based techniques [3, 4, 5], correlation-based outlier detection [6], cluster analysis-based outlier detection [7, 8] and ensemble techniques [9, 10]. When compared across huge data sets and hyper parameters, different methods have little systematic advantages over another in the measurement performance [11].

To classify types of anomalies at scale, we use different combinations of techniques starting with SVM and ending with CNN and LSTM sophisticated deep learning models.

The semantic transformation from a raw unstructured anomaly categorization task to a structured anomaly type classification task requires a solid background knowledge of the dataset, which features and instances are so different from the original raw data, namely the generation of a data view [12].

In fact, many practical anomaly detection problems often require a preprocessing in order to generate the appropriate data to handle with. The final step before the unsupervised anomaly detection algorithm can be applied is normalization. In practical applications, the min-max normalization is often used, every feature is normalized into a [0, 1] interval, so do we in the evaluation in this article

In this paper we present

## 2 Related Work

Sequences and time series data usually need different algorithms to detect anomalies [13]. P. Fiadino et al. [19] reported statistical detection and diagnosis of anomalies. Lazarevic et al. [14] compared LOF, k-NN, PCA and unsupervised SVM for intrusion detection. Ding et al. [15] studied SVDD, a k-NN classifier, k-means and a GMM for detecting anomalies. Amer et al. [16] proposed One-class Support Vector Machines for anomaly detection. The local density cluster-based outlier factor (LDCOF) [18] detect anomalies by estimating the clusters’ densities assuming a spherical distribution of the cluster members. Combining with multiple anomaly detection algorithms, outlier ensembles boost their joint detection performance [17]. In order to categorize the anomalies, we take the distributions of anomalies across the types described in table 1.

## 3 Method

We applied semantic data, derived from real system operation traces as suggested in []. The data in such format allows analyze the real-time system server operation with a large number of operational anomalies efficiently, moreover, it protects the sensitive information of system services. The procedure of generating semantic data and preprocessing are illustrated as following.

A label can be used as a result indicating whether an instance is an anomaly or not.

Let’s review discriminative algorithms from the perspective of application to finding various types of anomalies. The most suitable type of neural network working with time series is LSTM (Long Short-Term Memory) recurrent neural network, if properly built, it allows you to model the most sophisticated dependencies.

## 4 Experiments Settings

**Dataset**

Using a larger set of log data as input for a deep learning model is not always the best choice, as this increases the dimension of the input data, introducing sparsity issues. Therefore, it may negatively impact classification results. Meanwhile, irrelevant or redundant features will bring more noise to the overall process, thus models will obtain inferior performances.

The construction of the semantic dataset is conceived with the objective of fundamentally maintaining the underlying structural characteristics of the raw temporal operation data as much as possible. The dataset we considered spanning a period of a couple of months with consecutive days. The transformation procedure is described as follows. The first step of the construction procedure consists of manually labeling.

We divide this vector into m blocks, each one corresponding to a two-minute interval….

The dataset gained in this way retains certain features of real log data. It keeps the time-series variations of system operation, also, it maintains the differentiation among a variety of anomaly types.

**Modeling**

During months of trials, we successfully classify anomalies with high accuracy.

## 5 Results and Analysis

## 6 Conclusion

This area is still on-going research, and it requires a lot of work to build the model for the time series. Should you succeed, you may achieve outstanding performance results in terms of accuracy.

## Acknowledgments

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