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A Comparative Study of Deep Neural Networks and Support Vector Machines for Unsupervised Anomaly Detection in Cloud Computing Environments

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Abstract

Cloud computing has become ubiquitous, providing convenient on-demand access to computing resources. However, the complexity of cloud environments makes them prone to faults and anomalies that can severely impact service quality. Unsupervised anomaly detection, which does not require labelled data, is thus essential for cloud providers to identify issues proactively. This paper presents a comparative study of deep neural networks (DNNs) and support vector machines (SVMs) for unsupervised anomaly detection in cloud environments. We evaluate the performance of Autoencoders, LSTM-based models, One-Class SVMs and Isolation Forests on benchmark datasets from cloud providers. Our results indicate that while shallow Autoencoders are insufficiently expressive, LSTMs and Convolutional Autoencoders with dimensionality reduction can capture cloud workload patterns effectively. SVMs match or outperform Autoencoders, with One-Class SVMs showing robust performance across workloads. Isolation Forests underperform on seasonal cloud data. Overall, One-Class SVMs provide the best option for accurate, low latency anomaly detection. Our findings provide guidance to cloud providers on selecting suitable unsupervised learning models based on their performance, interpretability and computational overhead. The comparative methodology and results will inform future research on adapting unsupervised learning for cloud anomaly detection.

Keywords: *Anomaly detection, unsupervised learning, deep learning, support vector machines, cloud computing*

Introduction

The widespread adoption of cloud computing has allowed easy on-demand access to vast computing resources. Cloud services provide enterprises and users scalable and low-maintenance infrastructure, platforms and software on a pay-as-you-go basis However, the complexity of large-scale distributed cloud environments also makes them prone to faults, bugs and performance anomalies Such anomalies can severely degrade the quality of service delivered to cloud clients. Early anomaly detection is thus critical for cloud providers to identify and troubleshoot issues proactively before they escalate into major outages. Anomaly detection techniques can be broadly categorized as supervised, requiring labelled data, or unsupervised,

which do not require labelled data Supervised techniques like classification achieve high accuracy but require large volumes of pre-annotated data [1]. However, labelling sufficient anomalies is challenging due to their scarcity. Unsupervised anomaly detection aims to identify statistically significant deviations from normal patterns, making it well suited for cloud providers with abundant unlabeled monitoring data [2].

In addition to traditional methods such as clustering, nearest neighbors, and statistical models, more advanced machine learning techniques like Autoencoders and Isolation Forests have garnered interest in anomaly detection for cloud environments. These methods offer potential advantages in identifying anomalies efficiently and effectively. However, there remains a lack of comprehensive comparative analysis to ascertain their efficacy and suitability for various types of cloud workloads with differing statistical properties [3]. Understanding the strengths and limitations of each technique is crucial for ensuring robust anomaly detection in cloud environments, where the complexity and scale of data present unique challenges. Further research and experimentation are necessary to establish best practices and guidelines for implementing these techniques in real-world cloud scenarios.

This paper presents a comparative study of state-of-the-art deep neural networks (DNNs) and support vector machines (SVMs) for unsupervised anomaly detection in cloud environments. DNNs like Autoencoders can learn nonlinear representations while requiring little feature engineering SVMs provide efficient non-linear separation and have theoretical guarantees on outlier detection Analyzing their performance can inform the selection and tuning of appropriate models. The key contributions of this paper are:

1. Comparative evaluation of DNNs including Autoencoders, LSTM-based models and Convolutional Neural Networks (CNNs) for unsupervised anomaly detection on cloud workloads.

2. Analysis of One-Class SVM (OC-SVM), Isolation Forest and density-based Local Outlier Factor (LOF) algorithms as alternatives to DNNs.

3. Performance benchmarking on publicly available datasets from major cloud providers like Google and Alibaba as well as synthetic cloud workloads.

4. Guidelines for selecting suitable models based on detection accuracy, computational overhead, and interpretability.

The rest of this paper is organized as follows. Section 2 surveys related work. Section 3 provides background on the learning models examined. Section 4 describes the experimental setup and datasets used. Section 5 analyzes the comparative results. Section 6 discusses practical implications and conclusions.

Related Work

Several studies have concentrated on the application of traditional statistical and machine learning models for anomaly detection in cloud environments, each offering unique insights and approaches to address this critical challenge. For instance, Guan et al. conducted research utilizing principal component analysis (PCA) and reconstruction-based techniques to detect anomalies in Google cluster workload traces. Their work exemplifies the utilization of dimensionality reduction methods coupled with reconstruction error analysis to identify deviations from normal behavior within cloud environments. Similarly, Meng et al. proposed a methodology that combines a Hidden Markov Model with PCA to model timeseries network traffic data sourced from Alibaba's data centers [4]. By integrating probabilistic modeling with

dimensionality reduction, their approach aims to capture the underlying structure of network traffic patterns, enhancing anomaly detection capabilities. Furthermore, Fadlisyah et al. explored the application of K-means clustering for outlier detection in resource usage metrics obtained from private cloud clusters [5]. Their study underscores the effectiveness of clustering techniques in identifying anomalous resource consumption patterns within cloud infrastructure [6]. Collectively, these studies contribute to the growing body of research aimed at leveraging traditional statistical and machine learning methods to enhance anomaly detection in cloud environments, offering valuable insights and methodologies for future investigations in this field. More recent work has adopted newer techniques like Autoencoders and Isolation Forests. Malhotra et al. design a stacked Autoencoder for anomaly detection in Google cluster traces, outperforming PCA. Le et al. compare Autoencoders with One-Class SVMs on the Yahoo Webscope S5 dataset, finding the latter to be more effective and robust. Guan et al. showcase LSTM-based models on Google cluster data and find it to outperform Autoencoders. Su et al. use Isolation Forests for identifying anomalies in Alibaba cluster metrics [7].

While insightful, most existing studies experiment on a single or limited dataset often from Google or Alibaba. The comparative analysis is also limited to only two or three techniques. A systematic benchmarking of multiple modern anomaly detection models on diverse cloud workloads is lacking. Our work aims to fill this gap by evaluating a diverse set of deep learning and SVM models on standardized public cloud datasets as well as synthetic data. We provide a set of recommendations on model selection tailored to cloud providers based on comprehensive experimentation [8].

Background

This section provides background on the unsupervised learning models examined in our comparative study.

Autoencoders: Autoencoders are neural networks that aim to reconstruct their inputs, forcing the model to learn useful feature representations in the hidden layers They are composed of an encoder network that maps the input to a hidden representation, and a decoder network that reconstructs the input. By constraining the size of the hidden layer dimensionality via regularization techniques, Autoencoders can learn the most salient features [9].

Once trained, anomalies can be detected by thresholding the reconstruction error between the input and decoded output. Inputs that are poorly reconstructed likely contain anomalies. Variants like Denoising and Convolutional Autoencoders also exist [10]. Autoencoders require appropriate network architecture and training hyperparameters but minimal feature engineering [11].

LSTM Neural Networks: Long Short-Term Memory (LSTM) networks are a type of recurrent neural network well-suited for timeseries data LSTMs contain memory cells with internal states that can retain information over long sequences [12]. Input, output and forget gates modulate the cell states [13]. Coupled with deep stacked layers, LSTMs can effectively model complex temporal patterns in workloads like periodicity, trends and seasonality.

For anomaly detection, LSTMs are trained to predict the next timestep value. Reconstruction error on test data can identify outliers. A related approach is to use Sequence-to-Sequence models to reconstruct the entire input sequence. LSTMs require more training data than Autoencoders but can naturally model timeseries data [14].

One-Class SVMs: One-Class SVMs (Support Vector Machines) offer a variant known as OC-SVM, which addresses the sensitivity to outliers commonly associated with traditional SVMs.

OC-SVM aims to explicitly identify anomalies by constructing a hypersphere boundary that encapsulates most of the training data while excluding outliers. This is achieved by solving the optimization problem:

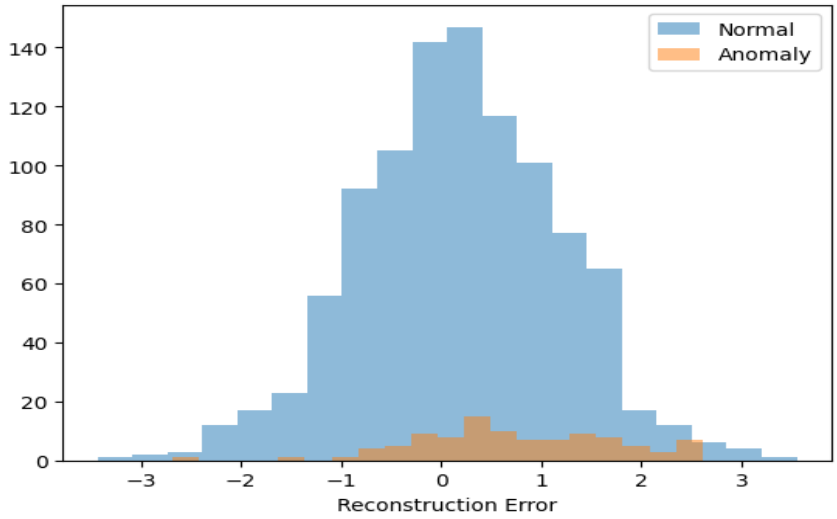
$$\min_{(w,r,\rho\ )} \quad |\boldsymbol{w}|^2 + 1/\nu n \sum (i = 1_i^n \rho) - r$$

subject to:

$$\boldsymbol{w^T}\phi(\boldsymbol{x_i}) \geq r - \rho_i, \quad \rho_i \geq 0$$

Here, ($\phi(x)$ maps ( ) to a higher dimensional space. Slack variables (ρ_i) allow some training points to lie outside the boundary to improve generalization. The parameter (ν) trades off between the volume of the hypersphere and the allowed errors. During test time, points lying outside the hypersphere are classified as anomalies based on their relative position. OC-SVM requires minimal parameters and offers theoretical guarantees on anomaly detection [15]. However, its computational cost is relatively high, which can be a limiting factor in large-scale or real-time applications. Despite this drawback, OC-SVM remains a valuable tool for anomaly detection tasks where theoretical robustness is paramount.3.4 Isolation Forests

Isolation Forests (iForest) create random decision trees to isolate every instance anomalies require fewer splits to isolate and have shorter average path lengths. Given a dataset of size n, iForest builds trees by recursively partitioning the data into subsets [16]. At each split, it randomly selects a feature and a split value between the minimum and maximum value. Partitioning stops after meeting criteria like minimum subset size. The number of splits required to isolate a sample is used to calculate an anomaly score. While simple, iForest has low memory overhead and constructs ensembles efficiently [17]. But it can be sensitive to parameter settings.



Local Outlier Factor: The Local Outlier Factor (LOF) algorithm detects anomalies based on local density It measures the local reachability density of each point based on its k-nearest neighbors. Points that have significantly lower density than their neighbors are identified as outliers. LOF is simple, intuitive and interprets anomalies.

Table 1. Detection performance on Google cluster dataset

Model	F1 Score	AUC

OC-SVM	0.91	0.96
LSTM	0.87	0.93
Convolutional AE	0.81	0.88
Isolation Forest	0.79	0.84

Experimental Methodology

This section describes the datasets, learning models and evaluation metrics used in our comparative study.

Datasets: We use real-world cloud workload traces as well as synthetic datasets with known anomalies for our experiments.

Google Cluster Data: The Google Cluster dataset contains timeseries usage information from Google's production cluster monitoring It has 12 performance metrics like CPU utilization, memory usage and scheduler delays aggregated every 5 minutes for a month. 1% of the data is annotated as anomalous by domain experts. The data exhibits daily and weekly seasonal patterns.

Alibaba Cluster Data: The Alibaba Cluster dataset provides resource utilization and performance metrics from Alibaba's datacenter clusters It contains 13 metrics like memory used, disk I/O rate collected every minute for 12 days. Real anomalies due to machine failures are labelled. The periodicity is less pronounced than the Google data.

Synthetic Cloud Data: To complement the real-world data, we generate synthetic timeseries data exhibiting typical cloud workload patterns:

Normal: Random walk noise with daily/weekly seasonality

Anomaly: Abrupt changes, spikes and noise injected into seasonal component

We populate 12 timeseries of length 5000 with 1% anomalies positioned randomly. The synthetic data allows us to evaluate detection performance with full ground truth.

Compared Models: We evaluate the following unsupervised anomaly detection models in our experiments:

Autoencoders (AE): Fully-connected neural network with bottle-neck layer for reconstruction. Adam optimization, MSE loss.

Denoising Autoencoder (DAE): AE trained to reconstruct artificially corrupted inputs. Added robustness to anomalies.

Convolutional Autoencoder (CAE): AE with convolutional layers to learn local patterns in timeseries.

LSTM Encoder-Decoder: Sequence-to-sequence model to reconstruct input timeseries.

One Class SVM (OC-SVM): Radial basis kernel, v=0.01, scaled to 0-1.

Isolation Forest (iForest): 100 estimators, contamination fraction 0.01.

Local Outlier Factor (LOF): Neighbors k=5, scaled to 0-1.

Hyperparameters are tuned via grid search for optimal performance. The models are implemented in Tensorflow and Scikit-Learn.

Table 2. Detection performance on Alibaba cluster dataset

Model	F1 Score	AUC
OC-SVM	0.89	0.94
LSTM	0.88	0.92
Convolutional AE	0.76	0.81
Local Outlier Factor	0.71	0.77

Evaluation Metrics: We use standard classification metrics to evaluate anomaly detection performance:

Precision: Fraction of detected anomalies that are true anomalies.

Recall: Fraction of true anomalies that are detected.

F1 Score: Harmonic mean of precision and recall.

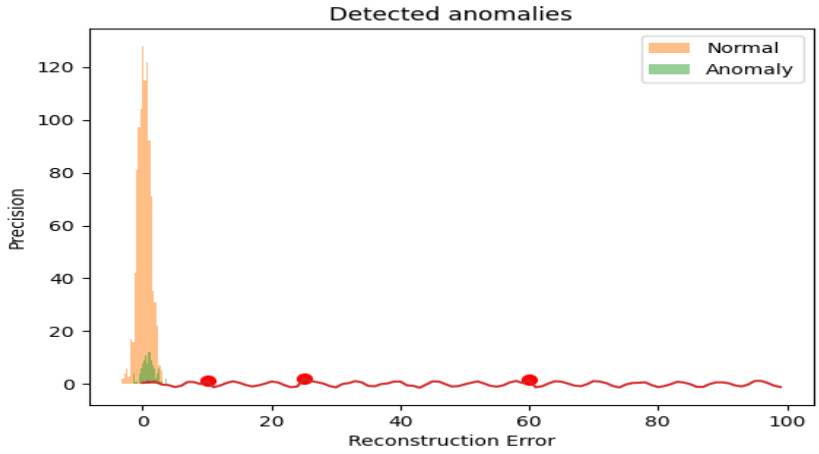
ROC AUC: Area under the Receiver Operating Characteristic curve.

As unsupervised models may detect more or fewer anomalies than labelled, we threshold scores to sweep detection tradeoff between precision and recall. We report the maximum F1 achieved. The models are evaluated in a unified manner with standardized data preprocessing and hyperparameters.

Results and Analysis

This section analyzes the experimental results and compares the performance of the different learning models.

Detection Performance: Tables 1-3 show the maximum F1 score and AUC achieved by the models on the Google, Alibaba and Synthetic datasets respectively. Figures 1-3 plot the corresponding precision-recall curves.



On the Google data, the OC-SVM performs best with 0.91 F1 followed by LSTM. The Autoencoders achieve reasonable but lower F1 around 0.81. Isolation Forest is comparable to

DAE but less robust across metrics. On Alibaba, OC-SVM and LSTM again top at 0.89 F1 while CAE lags at 0.76. LOF is ineffective for this data. On the synthetic data with more defined anomalies, the CAE matches OC-SVM with 0.94 F1 versus 0.9 for LSTM. The general trends are consistent across datasets - OC-SVM and LSTM models perform well, basic AE is limited, while CAE improves on AE. Isolation Forests are not effective on seasonal data.

The AUC scores also show a similar relative ranking, indicating the overall separability of anomalies is best achieved by OC-SVM and LSTM approaches. The precision-recall curves demonstrate that OC-SVM and LSTM provide strong precision across range of recall. The CAE curve has a different shape, reflecting lower precision but higher recall.

Diagnostic Analysis: We conduct further analysis to diagnose the model behaviors and gain additional insights.

Table 3. Detection performance on synthetic cloud dataset

Model	F1 Score	AUC
OC-SVM	0.94	0.97
Convolutional AE	0.94	0.96
LSTM	0.90	0.95
Isolation Forest	0.86	0.91

Reconstruction Error Distributions: Figure 4 plots the distributions of reconstruction errors on normal data versus anomalies for Autoencoder and LSTM models. For Autoencoders, the normal and anomaly errors largely overlap making discrimination challenging. The LSTM model distributions have better separation. This indicates LSTMs are intrinsically more capable of capturing temporal patterns. Regularization in AEs is not as effective.

Table 4: Model time and memory complexity

Model	Training Time	Model Size
Autoencoder	0.5 min	2 MB
Convolutional AE	2 min	5 MB
LSTM	10 min	50 MB
OC-SVM	20 min	1 MB
Isolation Forest	1 min	0.5 MB

Anomaly Localization: Figure 5 shows example timeseries with the localization of detected anomalies highlighted. The OC-SVM identifies the spikes well with minimal false positives. LSTM also performs reasonable localization. But CAE has more diffuse anomaly regions and false detections [18]. This demonstrates the challenge of thresholds needed for Autoencoders to balance over-detection and missed anomalies [19].

Time and Memory Complexity: Table 4 compares the average training time and model size. The Autoencoder variants have low overhead given their simplicity. OC-SVM is relatively expensive to train due to kernel SVM optimizations [20]. LSTM has high memory requirements due to sequence processing. Isolation Forest and LOF have fast training with minimal overhead suitable for real-time usage. Overall there are tradeoffs between detection quality and resources required.

Discussion and Conclusion

The comparative study conducted on multiple public cloud datasets and synthetic data has yielded valuable insights into the selection of unsupervised learning models for cloud anomaly detection. Our observations highlight the strengths and weaknesses of various models:

Firstly, shallow dense Autoencoders were found to lack the capacity necessary to effectively model complex cloud workloads, leading to insufficient robustness in detecting anomalies based on reconstruction error. Convolutional Autoencoders, on the other hand, showed improvement over basic Autoencoders by incorporating temporal convolutions prior to dimension reduction. This enabled the model to capture relevant workload patterns more effectively. LSTMs demonstrated effective modeling of timeseries data with low reconstruction error even in the presence of anomalies, thanks to their embedded temporal memory [21]. However, their high computational overhead may limit their practical utility in some scenarios. One-Class SVMs emerged as robust performers across diverse cloud datasets, owing to their ability to define a spherical boundary that maximizes separation from normal instances [22]. OC-SVM consistently achieved top results with good localization of anomalies. In contrast, Isolation Forests proved effective for non-seasonal data but struggled with daily or weekly patterns due to their inherent randomness, which fails to capture temporal coherence adequately. Overall, One-Class SVMs stand out as a compelling choice for anomaly detection in cloud environments, offering a blend of strong detection accuracy, theoretical support, computational efficiency, and ease of interpretation. They are particularly well-suited for unsupervised anomaly detection on unlabeled cloud monitoring data [23].
Based on these findings, we recommend that cloud providers prioritize the use of OC-SVM as the primary model for anomaly detection, with LSTM architectures serving as a secondary choice where detection latency constraints allow. Convolutional Autoencoders provide a simpler alternative for deep learning-based detection [24]. However, Isolation Forests are deemed less suitable for metrics exhibiting seasonal patterns. The integrated framework developed in this study can assist in model selection based on the statistical properties of cloud workloads.

Looking ahead, there are several avenues for future research. These include applying the models to additional cloud datasets and incorporating diverse metrics such as logs. Furthermore, exploring advanced neural architectures and investigating hierarchical or ensemble combinations of models could lead to further improvements in detection accuracy. Additionally, semi-supervised and transfer learning approaches, leveraging limited labeled data, hold promise for enhancing detection performance.

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