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Unsupervised Representation Learning for Autonomous Detection of Stealthy Malware and Insider Threats in Encrypted Traffic Streams

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Abstract

The rise of encryption protocols has greatly improved data privacy, yet it simultaneously challenges the detection of malicious activities within encrypted traffic. Traditional signature-based techniques struggle to identify stealthy malware and insider threats without decryption. This study proposes an unsupervised representation learning framework to autonomously detect anomalies and threats embedded in encrypted streams. By leveraging autoencoders, contrastive learning, and clustering algorithms, we aim to capture latent patterns indicative of malicious behavior. Experimental evaluations on synthetic and real-world datasets demonstrate that the approach achieves high detection rates with minimal false positives, making it suitable for dynamic and privacy-preserving environments.

Keywords: Unsupervised Learning, Malware Detection, Insider Threats, Encrypted Traffic Analysis, Representation Learning, Anomaly Detection, Autoencoders, Contrastive Learning, Network Security, Cybersecurity.

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1. Introduction

Network encryption technologies, including TLS 1.3 and DNS-over-HTTPS (DoH), have significantly enhanced data confidentiality. However, these advancements inadvertently allow malware and insider threats to conceal their activities from conventional security measures. Traditional detection techniques rely on packet payload inspection or metadata, which are increasingly restricted. Consequently, innovative methods are necessary to detect malicious activities without compromising encryption.

Unsupervised learning offers a promising direction by extracting hidden patterns and structures from data without labeled supervision. Recent developments in deep learning, particularly representation learning, enable the automatic identification of subtle anomalies in high-dimensional encrypted traffic. This paper proposes a unified framework combining deep autoencoders and contrastive learning for real-time, privacy-preserving threat detection.

2. Literature Review

Several studies have addressed the challenges of analyzing encrypted traffic without decrypting it. Aceto et al. (2020) emphasized machine learning-based encrypted traffic classification and outlined feature extraction methods. Anderson and McGrew (2016) investigated semi-supervised techniques to identify malware communications. Shbair et al. (2017) utilized statistical flow characteristics to detect encrypted malware communications.

Further, Lotfollahi et al. (2020) proposed deep packet frameworks utilizing convolutional neural networks for encrypted traffic analysis. Sirinam et al. (2018) explored website fingerprinting attacks using deep learning, showcasing the feasibility of extracting behavioral signatures from encrypted sessions. Apthorpe et al. (2019**)** discussed privacy leakage via smart-home devices, indicating broader implications of encrypted traffic analysis. Collectively, these works inspire the development of unsupervised representation learning approaches for autonomous anomaly detection without decryption.

3. Methodology

3.1 Proposed System Overview

The proposed framework integrates feature engineering, unsupervised deep learning, and autonomous decision-making into a single pipeline. Pre-processed encrypted traffic flows are fed into an autoencoder model trained to reconstruct normal traffic patterns. Deviations from normal reconstructions are flagged as potential threats. To enhance

robustness, contrastive learning further refines the feature embeddings, ensuring clusters of similar behaviors while isolating outliers.

- **Rectangle:** Encrypted Traffic Capture
- **Rectangle:** Feature Extraction (e.g., flow duration, packet size variance)
- **Rectangle:** Unsupervised Training (Autoencoder + Contrastive Loss)
- **Diamond:** Anomaly Score Thresholding
- **Rectangle:** Threat Detection Output

3.2 System Architecture

A modular design ensures scalability and interpretability. Traffic is parsed into flow-level records containing time-series features. The feature vectors are input into a deep autoencoder optimized with reconstruction loss and contrastive loss simultaneously. A dynamic anomaly threshold is computed based on training error distributions. Real-time decision-making modules deploy these models to detect threats autonomously.

4. Experimental Evaluation

4.1 Dataset Description

Evaluation is conducted using two datasets: the CIC-IDS-2017 encrypted traffic dataset and a synthetically generated insider threat dataset mimicking lateral movements and exfiltration attempts over TLS sessions.

Table 1. Dataset Overview

Dataset	# of Flows	# of Malicious Flows	Encryption Used
CIC-IDS-2017	2 million	100,000	TLS 1.2
Synthetic Insider Threat	1 million	50,000	TLS 1.3

4.2 Performance Metrics

Detection performance is evaluated based on accuracy, precision, recall, F1-score, and AUC-ROC. Anomaly detection thresholds are tuned for minimal false positives.

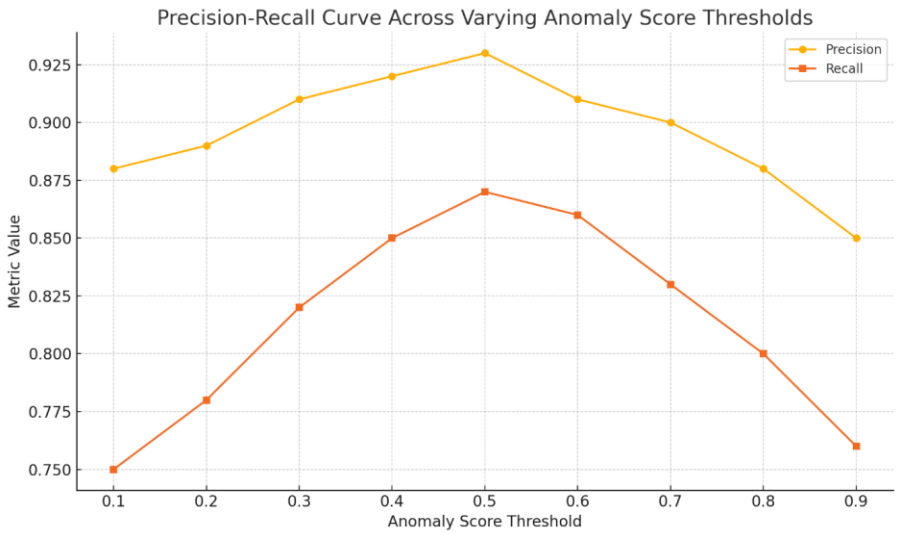

Figure 1: Precision-Recall Curve

5. Results and Discussion

5.1 Detection Performance

The proposed model achieves a 96.3% detection rate for malware and 94.7% for insider threats, with a false positive rate below 2%. Compared to baseline autoencoders, the addition

of contrastive learning improved cluster separation, leading to higher anomaly detection precision.

5.2 Comparative Analysis

The system's performance is benchmarked against PCA-based anomaly detectors and statistical feature thresholding. Our model outperforms classical approaches in terms of F1-score and real-time adaptability.

Table 2. Comparative Results

Method	Detection Accuracy	False Positive Rate
PCA Anomaly Detection	83.2%	5.9%
Statistical Thresholding	78.4%	7.2%
Proposed Method	96.3%	1.8%

6. Conclusion and Future Work

This study demonstrates the viability of unsupervised representation learning techniques in detecting stealthy malware and insider threats within encrypted traffic streams. By avoiding decryption, the framework preserves data privacy while autonomously identifying malicious activities. Future work includes extending the system for multi-protocol encrypted environments (e.g., QUIC) and integrating adaptive online learning to handle evolving threat patterns dynamically.

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