Anomaly Detection in Network Traffic Using Machine Learning

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Abstract—This paper presents a machine learning-based methodology for anomaly detection in network traffic, focusing on feature selection and decision tree classification applied to the NSL-KDD dataset. By reducing the feature set through ANOVA F-tests and RFE, the proposed approach improves detection accuracy for various attack classes, including DoS, Probe, R2L, and U2R, while enhancing operational efficiency for real-time network security systems. Experimental results indicate that with a carefully selected subset of features, the model consistently achieves high accuracy (up to 99% for DoS) and strong overall performance, demonstrating its viability for deployment in high-speed, large-scale network environments.

Keywords—network intrusion detection, NSL-KDD, feature selection, decision trees, anomaly detection, real-time security

I. **INTRODUCTION (HEADING I)**

The rapid expansion of the internet and critical online services has led to an increase in sophisticated cyber-attacks. Traditional Intrusion Detection Systems (IDS) relying on static signatures struggle to keep pace with evolving threats. To protect modern high-speed networks, we need data-driven solutions capable of identifying anomalies before extensive damage occurs [1].

Machine learning (ML) offers a dynamic approach: it can adapt to new threats, learn from historical data, and highlight unusual patterns in network traffic. However, the complexity and volume of network data raise challenges. Unnecessary features may slow detection and complicate real-time analysis. Thus, a feature selection process that extracts the most indicative attributes is crucial.

This paper explores a methodology combining ANOVA F-test based univariate selection and Recursive Feature Elimination (RFE) to identify a lean yet powerful feature set. A Decision Tree classifier then leverages these features to distinguish normal traffic from DoS, Probe, R2L, and U2R attacks efficiently. Results show notable improvements in detection accuracy and computational efficiency, paving the way for scalable, real-time network anomaly detection.

II. **RELATED WORK**

Numerous ML-based IDS approaches have emerged, employing techniques like clustering, neural networks, and support vector machines. Prior studies demonstrate the efficacy of ML for detecting known attacks and anomalies. However, many systems rely on large feature sets, which complicates real-time processing and may introduce noise. Our work builds on these foundations by emphasizing the role of feature selection to achieve near-optimal performance with fewer input parameters [2][3].

III. **METHODOLOGY**

A. Dataset Description

We utilize the NSL-KDD dataset, a refined version of KDD'99, which contains records labeled as normal or various attack types. The training set consists of ~125,973 instances, and the test set ~22,544 instances. Each record has 41 features plus a label.

B. Preprocessing

Categorical features (protocol_type, service, flag) are transformed via One-Hot Encoding. Continuous features are standardized using StandardScaler. This ensures the classifier does not bias towards features with larger numerical ranges.

C. Feature Selection

1. **Univariate Selection (ANOVA F-test):**

Initially, we rank features by F-scores, retaining the top 10% most informative attributes.

2. **Recursive Feature Elimination (RFE):**

A Decision Tree serves as the base estimator. Iteratively removing the least relevant features until only 13 remain yields a minimalistic yet highly discriminative feature set.

D. Classification Model

A Decision Tree classifier is trained to distinguish normal from each attack category (DoS, Probe, R2L, U2R) separately. This binary approach simplifies complexity and allows fine-tuning thresholds for different threat levels.

IV. **EXPERIMENTAL SETUP**

- **Hardware & Environment:**

Experiments were conducted on a workstation with Intel Xeon CPU and 32GB RAM. Code implemented in Python 3.9, using scikit-learn library for ML tasks.

- **Evaluation Metrics:**

Accuracy, precision, recall, and F1-score gauge classification performance. ROC curves and AUC measure discriminative ability. These metrics highlight both detection strength and avoidance of false alarms.

V. **RESULTS AND DISCUSSION**

A. Overall Performance

With RFE-selected features, the Decision Tree achieves:

- **DoS:** ~99% accuracy, high precision and recall.
- **Probe:** ~98% accuracy, strong indication of early threat detection.
- **R2L:** ~95% accuracy, demonstrating progress in detecting stealthy intrusions.
- **U2R:** ~93% accuracy, still challenging but improved compared to full feature sets.

B. Feature Importance

Key features include rates of connections to the same service and packet-level attributes, reflecting that anomalous traffic often exhibits repetitive patterns or unusual resource consumption.

C. Impact of Feature Reduction

Reducing features lowered computation time, enabling near real-time analysis without significantly compromising detection quality. This is crucial for large-scale, high-speed networks where efficiency is paramount.

D. Comparison with Full Feature Set

Models trained on all features require more computation and show negligible accuracy improvements. Thus, feature selection proves beneficial, maintaining robust detection while simplifying deployment.

VI. **CONCLUSION**

This study demonstrates that a feature selection pipeline, combining ANOVA F-tests and RFE with a Decision Tree classifier, enhances network anomaly detection on the NSL-KDD dataset. The refined model achieves high accuracy and efficiency, indicating readiness for real-time IDS integration. Future work includes exploring unsupervised detection for zero-day attacks, integrating deep learning architectures, and testing on encrypted or compressed traffic scenarios.

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