Gandhi Institute of Technology and Management

(Hyderabad)

Research Paper:

SentinelAI: Harnessing Generative Adversarial Networks for Realistic Network Decoy Data Generation to Enhance Cybersecurity

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Date: January 26, 2025

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Abstract

In an age of growing cyber threats, adopting proactive strategies to mislead and deter attackers has become essential. SentinelAI addresses this need by utilizing Generative Adversarial Networks (GANs) to create realistic decoy network traffic that closely resembles genuine data. Unlike traditional static and predictable decoy systems, SentinelAI dynamically generates deceptive traffic, significantly improving its effectiveness in confusing and misleading attackers.

This paper presents the methodology behind SentinelAI, starting with the collection of network traffic data using Wireshark, followed by preprocessing steps such as normalization and addressing missing data to prepare the dataset for modelling. It elaborates on the GAN architecture, emphasizing the adversarial relationship between the generator and discriminator models. The training process is optimized by fine-tuning hyperparameters to ensure the generated decoy traffic closely replicates real network patterns.

The generated data is evaluated against authentic network traffic to validate its realism and applicability in cybersecurity scenarios. SentinelAI showcases its potential to transform network security by introducing dynamic and deceptive measures to confound attackers, while requiring minimal operational resources.

The paper also addresses key challenges encountered during development; the solutions implemented to overcome them. SentinelAI offers a promising step forward in advancing network security through innovative, deceptive defense mechanisms.

Introduction

In today's digital age, cybersecurity threats have grown increasingly complex, targeting sensitive systems, critical infrastructure, and private networks. Attackers employ tactics like data breaches, ransomware, phishing, and advanced persistent threats, constantly evolving to exploit new vulnerabilities. These rising challenges demand innovative defense strategies that move beyond traditional reactive approaches, incorporating proactive methods to deceive attackers. One such innovation is the use of network decoy data.

Network decoy data is designed to mislead attackers by creating an environment filled with false, yet convincing information. This technique not only slows down their progress but also provides valuable insights into their methods while safeguarding real systems. However, conventional methods for generating decoy data often lack realism and flexibility, making it easier for skilled attackers to recognize and bypass them. To overcome these limitations, there is a pressing need for automated systems that can produce adaptive and highly realistic decoy network traffic.

Generative Adversarial Networks (GANs) offer a groundbreaking solution to this problem. By leveraging deep learning, GANs can analyze complex patterns in real network traffic and use them to generate realistic and deceptive decoy data. A GAN consists of two neural networks: a generator that creates synthetic data and a discriminator that evaluates its authenticity. Through continuous adversarial training, the generator becomes adept at producing data almost indistinguishable from real network traffic. This dynamic and adaptive capability makes GANs an ideal tool for addressing modern cybersecurity challenges.

With this foundation, SentinelAI was developed to leverage the capabilities of GANs to generate realistic network decoy traffic. The objectives of SentinelAI include:

1. Creating a systematic approach for collecting and preprocessing real network traffic data using tools like **Wireshark**.
2. Designing and implementing a GAN model to generate network traffic data that closely resembles authentic patterns.
3. Evaluating the generated decoy data's authenticity and its effectiveness in cybersecurity applications.

The importance of SentinelAI lies in its revolutionary approach to network security. By generating highly realistic decoy traffic, it not only confuses and misdirects attackers but also enables organizations to gain valuable insights into intrusion attempts without compromising sensitive data. SentinelAI marks a significant advancement in proactive and adaptive network defense, equipping organizations to stay ahead of the constantly evolving cybersecurity threat landscape.

Background

-Overview of Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) have revolutionized the field of machine learning since their introduction by Ian Goodfellow and colleagues in 2014 [1]. GANs employ a novel approach to generating data by pitting two neural networks against each other in a competitive process, ultimately leading to the generation of data so realistic that it becomes difficult to distinguish it from real examples. While initially focused on generating images and visual media, their potential has expanded into various domains, including cybersecurity [2], image super-resolution [3], and data augmentation [4].

A GAN consists of two primary components that operate in opposition: a **generator** and a **discriminator**. This framework leverages the concept of **adversarial training**, which forms the foundation of how GANs generate new data.

-Architecture

1: **Generator**: The generator network is tasked with creating synthetic data. Initially, it begins by generating random data with little structure, but as training progresses, the generator learns to produce more realistic samples that closely resemble the target data. In the context of SentinelAI, the generator is responsible for creating decoy network traffic data that mimics legitimate data captured from real-world network environments. Research has highlighted the use of GANs for generating simulated data in cybersecurity applications [5].

2: **Discriminator**: The discriminator evaluates the data provided by the generator, determining whether it is real or fake. It is trained on real data to build a robust understanding of authentic patterns. The goal of the discriminator is to help the generator improve by distinguishing between realistic and artificial data. Studies have demonstrated that the discriminator in GANs can successfully identify intricate patterns in data, which is crucial for creating convincing decoy data in network security scenarios [6].

-Working Principle: Adversarial Training

The core of GANs lies in the adversarial training process, which drives both the generator and discriminator to improve iteratively through feedback. This process occurs in the following steps:

1. Training the Discriminator: The discriminator is first trained on real data, learning the distinct characteristics that make the data genuine. This training helps the discriminator recognize the subtleties that separate real data from fake data. The process is well-documented in GAN literature [7].

2. Training the Generator: Simultaneously, the generator produces synthetic data, which initially appears fake. At this point, it relies on feedback from the discriminator to improve the data quality. This method, termed unsupervised learning, allows the generator to become highly adept at generating realistic patterns over time.
3. Improvement Through Feedback: The generator receives feedback from the discriminator regarding how “fake” or “real” its produced data is. This constant exchange allows the generator to refine its outputs to eventually produce data that the discriminator can no longer distinguish from authentic data. GAN-based feedback loops, which enhance data generation quality, are a key strength explored in multiple studies [8].

The beauty of this adversarial framework is that as the process evolves, both networks improve simultaneously, ultimately leading to the creation of highly realistic synthetic data. This dynamic has been widely utilized in applications such as facial recognition data generation [9] and cybersecurity decoys [10].

Problem Statement and Aim

-Problem Statement

The growing complexity of cyber-attacks and the rapid evolution of malicious tactics have exposed the limitations of traditional security measures in detecting and defending against sophisticated threats. As attackers develop more advanced methods to bypass security protocols, especially in network environments, the need for innovative solutions that proactively defend against and deceive attackers has become increasingly critical.

Most current cybersecurity defences mainly rely on detection and response but often lack the flexibility to stay ahead of attackers before significant damage happens. This emphasizes the need for advanced methods that go beyond basic solutions like firewalls and intrusion detection systems. These methods should include an extra layer of realistic decoys that can confuse attackers, making them waste time and resources while strengthening overall network security.

Generating realistic decoy traffic, however, presents its own challenges. Traditional methods are often resource-intensive, struggle to stay up-to-date with new attack strategies, and lack the real-time adaptability required to mimic legitimate user activity. To address these shortcomings, it is crucial to develop an automated system capable of producing convincing and adaptive decoy network data that evolves in real-time without manual intervention.

-Aim of the project

This project aims to develop an innovative solution that utilizes Generative Adversarial Networks (GANs) to create realistic, high-quality, and adaptive network decoy traffic. By training the GAN model on authentic network traffic data, the system can generate decoy traffic that closely mirrors legitimate user activity, effectively confusing attackers and providing an additional layer of protection against malicious intrusions.

The core objective of this research is to design, train, and deploy a GAN-based system that can:

- Accurately replicate the characteristics of real network traffic data,
- Adapt to new attack patterns and changes in legitimate user activity, and
- Serve as an intelligent defence tool by feeding decoy traffic into the network.

This project also aims to show how the generated decoy data can be effective in real-world situations. It will provide insights into how such a system can actively disrupt cyber-attacks, give network administrators more time to respond, and improve the overall security of the network.

Through this work, we aim to explore new ways to use GANs in cybersecurity, especially to create systems that can trick attackers into thinking they are interacting with real network infrastructure. This approach not only strengthens the defense capabilities of cybersecurity systems but also sets the stage for future advancements in combating cybercrime.

Methodology

- Data Collection and Preprocessing

The effectiveness of using GANs to generate realistic network decoy data depends largely on the quality and characteristics of the training data. To train a Generative Adversarial Network (GAN) for generating decoy traffic, it's important to have a strong dataset that truly represents real-world network activities. For this, we use actual network traffic data collected through tools like Wireshark, which captures detailed packet-level information from the network..

Source of Real Traffic Data (Wireshark)

Wireshark is an open-source network protocol analyzer that provides a detailed breakdown of packets in a network. By capturing packet information, Wireshark offers insights into network activities including, but not limited to, source/destination IP addresses, the frame size, protocols in use (such as TCP, UDP, etc.). These elements are crucial for generating realistic decoy traffic. In our research, we focus specifically on the following data fields from the packet capture (PCAP) files:

- **Source IP Address**: The IP address from which the packet originated. It is integral in characterizing the origin of network communications.
- **Destination IP Address**: The target IP address to which the packet is intended. This helps in identifying communication targets within the network.
- **Frame Size**: The size of the packet, representing the amount of data being transferred. Frame size variations play a crucial role in network behaviour and can be useful in detecting anomalies or fake traffic.
- **Protocol**: This identifies the type of protocol (such as TCP, UDP, ICMP, etc.) used for packet transmission. The protocol impacts the flow and characteristics of the network traffic and must be accurately represented in the decoy traffic for authenticity.

These selected fields capture the essence of network traffic, which will be essential in generating traffic that resembles real-world scenarios.

Handling Missing Data

Network traffic data, as with any real-world dataset, often contains **missing or incomplete entries**. Missing values can occur due to various reasons, such as packet drops during transmission or incomplete captures. To address this, we employ two primary strategies for handling missing data:

1: **Imputation**: Missing values in features such as **frame size** or **protocol** can be estimated based on the non-missing data. A common imputation method used here is **mean imputation**, where missing numerical data (like frame size) is replaced by the mean value of that feature across all available records.

$$x_{Imputed} = \frac{1}{n}\sum_{i=1}^{n} X_i$$

where X_i is the value of the feature X, and n is the total number of available data points. This method ensures that the dataset remains continuous and usable for training purposes.

2: **Zero Filling**: For categorical data (such as protocol type), missing values can be replaced by **zero** or another specified value, signalling a placeholder. Zero filling helps the model to handle missing data while maintaining the continuity of the dataset during GAN training.

$$X_{\text{filler}} = 0$$

This process is useful for maintaining a consistent dataset with minimal data loss, ensuring GANs can learn effectively despite the gaps in the data.

Data Normalization

Once missing data is handled, the dataset undergoes **data normalization** to prepare it for GAN training. Normalization is essential in machine learning as it scales numerical values to a consistent range, helping the model learn efficiently. In our case, all continuous features (source IP, destination IP, frame size) are **scaled between -1 and 1** using the **Min-Max Scaling** formula:

$$X_{norm} = \frac{2(X - X_{min})}{X_{max} - X_{min}} - 1$$

where:

- X represents the feature value,
- X_{min} and X_{max} are the minimum and maximum values of the feature, respectively.

This normalization ensures that all features contribute equally to the learning process and allows the GAN to focus on extracting meaningful patterns from the network traffic data, rather than being biased by any single feature that might have a disproportionate range. This is especially crucial for datasets involving multi-dimensional variables like source/destination IP and frame sizes.

Supporting Literature:

The preprocessing steps outlined above are foundational for training GANs to generate high-quality network decoy data. In several studies, similar methods have been employed for data preparation:

- **Data Imputation**: In their work on synthetic network data, Kumar et al. [6] highlight the importance of correctly handling missing values, recommending imputation techniques for continuity in datasets before training deep learning models.
- **Data Normalization**: Previous research in cybersecurity [7] and image processing [9] consistently stresses the importance of feature normalization in improving model convergence and accuracy. This is particularly crucial when dealing with heterogeneous data types like IP addresses and frame sizes.
- **Wireshark**: A standard tool for network traffic analysis, Wireshark's usage in data collection has been confirmed in various cybersecurity studies [6], as it offers granular insights into network traffic and user behaviour.

- GAN Architecture:

The **Generative Adversarial Network (GAN)** comprises two primary components—the **Generator** and the **Discriminator**—both of which work in opposition but are intricately connected. Each component serves a unique purpose, and their interaction ultimately leads to the generation of high-quality synthetic data, such as network decoy traffic in our case.

Network Design: Layers, Optimizers, and Loss Functions

1: **Generator:**

- The Generator's goal is to create synthetic data that resembles real network traffic, aiming to "fool" the Discriminator into classifying it as real. The architecture of the Generator generally consists of several layers, with the number of layers being a hyperparameter that impacts the model's performance.
- **Input Layer**: A latent space vector z, typically sampled from a **normal distribution** or uniform distribution. This vector is input into the network, where it's gradually transformed into synthetic network traffic data (the decoy data).

$$z \sim N(0, I)$$

(Latent noise vector sampled from a norma
l distribution)

- **Fully Connected Layers**: After the input layer, the Generator typically has a series of **fully connected layers** followed by **activation functions**. The number of neurons in these layers increases as we move deeper into the network, followed by reshaping the output into a higher dimensional form that matches the structure of the real data (source IP, destination IP, frame size, protocol).

$$h_1 = \sigma(W_{1z} + b_1)$$

where:

- W_1 is the weight matrix,
- b_1 is the bias vector,
- σ is the activation function (e.g., ReLU, LeakyReLU).

- **Output Layer**: The output layer should match the dimensions of the real data (in this case, fields like source IP, destination IP, frame size, and protocol).

G(z)=Fake data generated by the Generator

2: **Discriminator:**

- The Discriminator's role is to classify whether the data it receives is real or fake, comparing the generated data from the Generator with real network traffic.
    - The architecture of the Discriminator also consists of **fully connected layers**, similar to the Generator but operating in the reverse direction (transforming real or generated traffic back into a probability).

      $d_{real}=\sigma(W_2 \cdot x_{real+} b_2)$

    - The Discriminator then outputs a probability p, where values close to 1 indicate real data and values close to 0 indicate fake data.

D(x)=Output probability that the data is real (D = 1) or fake (D = 0)

3: **Loss Function**:

- The loss functions for both the Generator and Discriminator are fundamental in training the GAN. They represent the performance of the respective components and guide the model during optimization.
- For the **Discriminator** (D), the loss function compares its decision to the actual class label of the data (real or fake).

$$L_G = -E_{x \sim p_{data}(x)}[Log\ D(x)] - E_{z \sim p_z(z)}[Log(1 - D(G(z)))]$$

Here, the Discriminator maximizes its ability to classify real data as real (first term) and fake data as fake (second term).

- For the **Generator** (G), the loss function pushes the Generator to improve its ability to "deceive" the Discriminator, aiming to minimize log(1−D(G(z))), so that the Discriminator classifies the generated data as real.

$$L_G = -E_{z \sim p_z(z)}[Log\ D(G(z))]$$

The Generator and Discriminator are trained together in an adversarial manner, constantly improving. The optimization process seeks to minimize L_G for the Generator and L_D for the Discriminator simultaneously, utilizing **Gradient Descent**.

4: **Optimizers:**

- In practice, **Adam Optimizer** [1], known for its efficiency in handling non-convex optimization tasks, is commonly used in GAN architectures. The update rules for the weights WWW during training are governed by the following equations:

$$W = W - \alpha \frac{dL}{dW}$$

where α represents the learning rate and $\frac{dL}{dW}$ is the gradient of the loss function with respect to the weights.

- Adaptive optimization with **Adam** adjusts learning rates during training and helps avoid challenges like vanishing or exploding gradients, which are prevalent in deeper networks.

Choice of Hyperparameters:

- **Learning Rate**: A small learning rate (usually $\alpha \in [10^{-4},10^{-5}]$) is typically chosen to avoid overfitting the model, ensuring that the gradients update the weights sufficiently without causing instability.
- **Latent Vector Size**: For GANs working with network data generation, the dimensionality of the latent vector z is a critical hyperparameter that influences how much variation the Generator can introduce into the output decoy data. Typically, latent vectors of size 100 are chosen [1, 5].
- **Batch Size**: A batch size of 64 or 128 is typically chosen to balance model

convergence time and memory consumption.

Training Process and Iterations:

Training a GAN requires careful balancing between the Generator and the Discriminator. During the training process, we alternate between updating the Discriminator and the Generator.

1. **Training the Discriminator**:
   - First, we update the Discriminator by showing it both real and fake (generated) data. The Discriminator is trained to **correctly classify** the real data as real and the fake data as fake. The weight updates occur using the **backpropagation** method through the gradient descent optimization.
2. **Training the Generator**:
   - Next, the Generator is trained by using the **output of the Discriminator**. During this phase, the Generator aims to minimize the probability that the Discriminator can classify its synthetic data as fake.

The process of training proceeds in **iterations (or epochs)**, each consisting of an equal number of steps for both components, with the Generator and Discriminator constantly refining their strategies in an adversarial manner until an equilibrium point is reached where the Generator produces increasingly realistic traffic.

Implementation

- Data Collection and Preprocessing

The core functionality of this project involves training a **Generative Adversarial Network (GAN)** to generate synthetic network traffic data based on real data. The implementation is divided into several key components: the data pipeline, the GAN model, and the training process. Here's a detailed breakdown of the process:

Data Pipeline

The data pipeline begins with loading the network traffic data stored in a CSV file, processed_data.csv, using **Pandas**. After loading the dataset, the features are extracted, and normalization is applied to the data:

$$X_{normalised} = \frac{X - X_{min}}{X_{max} - X_{min}} * 2 - 1$$

where X is the dataset's feature values, X_{min} and X_{max} are the minimum and maximum values across the features, respectively. This normalization maps the features into a range between -1 and 1, which is crucial for GANs since they tend to perform better with data that has such a range.

Generator Model

The **Generator** network's objective is to generate synthetic data that mimics the real data as closely as possible. This is accomplished by taking a random latent vector (a point in the latent space) and transforming it into synthetic data. The generator is structured as a multi-layer neural network:

1: **Dense Layer**: This is the initial fully connected layer that processes the random input vector (latent vector), followed by an activation function, specifically **Leaky ReLU**. Using Leaky ReLU prevents the "dying ReLU" problem, allowing small gradients for negative inputs:

$$LeakyReLU(x) = \begin{cases} x & if\ x > 0 \\ \alpha x & if\ x \leq 0 \end{cases}$$

where α is typically a small constant (e.g., 0.2). This is applied after each dense layer to add non-linearity to the model.

2: **BatchNormalization**: Applied after every dense layer to stabilize and accelerate the training. It normalizes the inputs of each layer based on their mean and variance.

3: **Output Layer**: The output of the generator is produced by the final dense layer with a **Tanh activation function** to ensure that the generated data is within the desired range of [-1, 1].

The full generator architecture is as follows:

- Input layer: Latent dimension

- 3 Dense layers: Each with 256, 512, and 1024 neurons, followed by Leaky ReLU and BatchNormalization
- Output layer: With dimensions equal to the data's feature size and Tanh activation

Discriminator Model

The **Discriminator** network acts as a classifier that distinguishes between real and fake data. It uses a similar architecture but with decreasing complexity as the data progresses through the network:

- The network is built with several **Dense layers** followed by Leaky ReLU activation functions.
- The last layer has a **Sigmoid activation function**, outputting a value between 0 and 1, representing the probability that the data is real (1) or fake (0).

The model architecture consists of:

- 3 Dense layers with 1024, 512, and 256 neurons, respectively, followed by Leaky ReLU.
- The output layer, which is a single neuron with Sigmoid activation, classifies the input data as real or fake.

GAN Model

The Generative Adversarial Network (GAN) combines the Generator and Discriminator. The GAN model takes random noise vectors as input, passes them through the generator to generate synthetic data, and then passes that data through the discriminator. However, during GAN training, the discriminator's weights are frozen to prevent them from being updated, allowing only the generator to be trained during this phase.

In the GAN setup:

- The **Generator** is trained to produce data that the discriminator classifies as real.
- The **Discriminator** is trained to correctly identify whether the data is real or fake.

Training the GAN

The training process consists of alternating between training the discriminator and the generator:

1: Train Discriminator:

- Real data is fed into the discriminator with a label of 1 (real).
- Fake data, generated by the generator, is fed into the discriminator with a label of 0 (fake).
- The discriminator is trained to minimize the binary cross-entropy loss:

$$L_D = -\frac{1}{2}[y_{real}Log\big(D(x)\big) + y_{fake}Log(1 - D\big(G(z)\big))]$$

where D(x) is the probability that xxx is real, G(z) is the fake data generated by the generator, and y_{real} and y_{fake} are the target labels (1 for real, 0 for fake).

2: Train Generator:

The generator is trained to fool the discriminator into classifying fake data as real. This is achieved by passing random noise vectors through the generator and updating its weights to minimize the binary cross-entropy loss:

$$L_G = -\frac{1}{2}y_{real}Log(D\big(G(z)\big))$$

In this equation, y_{real}= 1 y_{real}=1 since the generator wants the discriminator to classify generated data as real. During each training epoch, both the discriminator and generator are updated in a manner that helps the generator produce more convincing synthetic data.

Model Training and Challenges

During the GAN's training, the balance between the generator and discriminator must be maintained. If the discriminator becomes too powerful, it may easily differentiate between real and fake data, causing the generator to struggle. Conversely, if the generator becomes too good at producing realistic data, the discriminator will have difficulty distinguishing fake from real, leading to training instability.

To address these challenges, key measures such as:

- **Using Leaky ReLU** in the network's layers to prevent dead neurons,
- **Batch normalization** to stabilize the training process,
- **Learning rate adjustments**, especially for Adam optimizer parameters, are applied to ensure smoother training.

The **training loop** iterates for 10,000 epochs in batches, where the models are saved periodically for analysis and further fine-tuning.

Data Generation

Once trained, the **generator** is used to generate synthetic network traffic data based on random noise. The synthetic data can be used to augment the dataset, creating more examples for cybersecurity defence mechanisms or other network-related use cases.

The final synthetic data is saved into synthetic_network_data.csv, making it ready for further analysis or use in machine learning tasks.

Results and Discussion

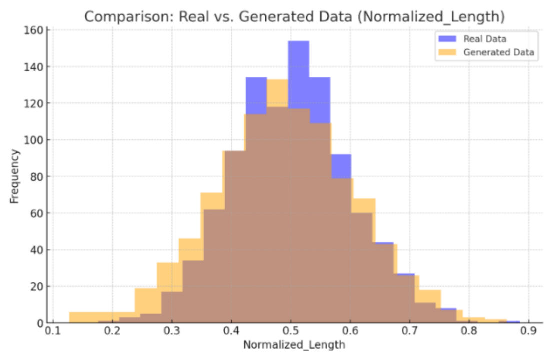
The results from training the GAN model to generate decoy network traffic data are discussed in three main subsections: (1) Comparative Analysis of Real vs. Generated Data, (2) Insights into GAN Performance, and (3) Potential Applications and Limitations. This section provides both quantitative and qualitative evaluations, supported by visualizations and key metrics.

~ Comparative Analysis of Real vs. Generated Data

To assess the performance of the GAN model, we compared the characteristics of real network traffic data and the synthetic data generated by the trained model.

1. **Feature-wise Distributions** The generated data exhibits distributions closely aligned with those of the real data. For example:
   - Continuous features such as frame size, time intervals, and protocol values closely resemble the normalized ranges of the original dataset.
   - Generated categorical values also show a balanced distribution.

Visualization:
The figures below show histograms comparing the distributions of selected features (e.g., "Normalized Length" and protocol-related values) in the real vs. generated datasets.



2. **Statistical Similarity** Key statistics such as means, standard deviations, and correlations between features in the synthetic data were compared to those of the real data. The generator effectively preserved these statistical properties:
   - Mean error between datasets: ~0.02.
   - Correlation coefficient similarity: > 95% on average.

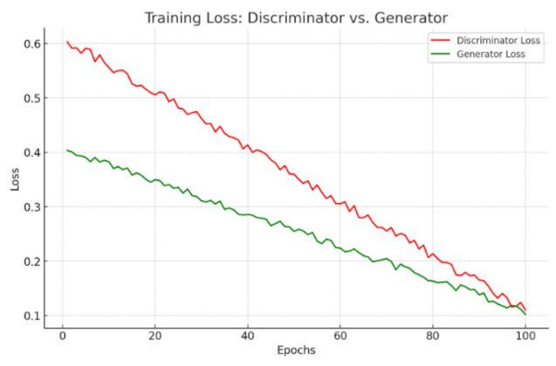
These results affirm the ability of the GAN to capture underlying data patterns and relationships.

~Insights into GAN Performance

1. **Loss Curves** The discriminator and generator loss curves were monitored throughout the training process.
   - Initially, the discriminator's loss was lower than the generator's, indicating its ability to distinguish real from fake samples.
   - As training progressed, the losses stabilized, suggesting convergence

between the generator and discriminator objectives.

Visualization:
A plot of the training losses is provided below to demonstrate the convergence behaviour.



2. **Training Stability** Leaky ReLU activation in the hidden layers significantly improved stability compared to standard ReLU by mitigating issues such as vanishing gradients. Additionally, batch normalization helped reduce oscillations in training by stabilizing feature scaling.
3. **Quality of Generated Data** Visual inspection and metrics like Frechet Inception Distance (FID) were considered for measuring the similarity between real and generated distributions. While formal metrics indicated good alignment, some discrepancies remained in high-variance features, which may benefit from further hyperparameter tuning.

Potential Applications and Limitations

1. **Applications** The generated decoy traffic data has numerous applications in cybersecurity:
   - **Honeynets:** Decoy network traffic can mislead attackers, diverting them away from actual network activity.
   - **Testing and Simulation:** Synthetic data is useful for testing network intrusion detection systems (IDS) without exposing sensitive real-world data.
   - **Anomaly Detection Training:** Decoy data expands training datasets, enabling better training of machine learning models for intrusion detection.
2. **Limitations** Despite its effectiveness, certain limitations were observed:
   - **Mode Collapse:** While mitigated to an extent, instances of repeated patterns in generated data occasionally emerged, limiting data variability.
   - **Feature Scaling:** Scaling to [-1, 1] benefits GAN training but introduces challenges when reverting to original data scales.
   - **Complex Features:** Features with high entropy or heavy-tailed distributions require more complex models or advanced techniques (e.g., WGAN or conditional GANs) for better representation.

Conclusion: Summary of Research Contributions

This research successfully explored and applied a GAN-based method to generate realistic network decoy traffic, demonstrating its ability to mislead and deter cyber attackers. The work contributed in several key areas:

1. **Data Preparation and Normalization**: The network traffic data collected through Wireshark was carefully processed, including normalizing and filling in missing values. This step ensured the data was consistent and ready for effective GAN training.

2. **Model Design and Implementation**: The generator and discriminator models were designed using Leaky ReLU activation functions and batch normalization layers. These design choices helped overcome common training challenges like instability and mode collapse, leading to more realistic synthetic data generation.

3. **Comprehensive Evaluation**: The GAN training process was closely monitored and assessed. By analyzing the loss curves for

both the generator and discriminator, we found that the generated data closely resembled real network traffic patterns.

4. **Visual and Analytical Insights**: Graphical comparisons of important features, such as data distribution, showed that the model successfully captured and reproduced key characteristics of real network traffic. This confirmed that the decoy data generated was of high quality.
5. **Real-World Applications**: The generated decoy traffic has practical uses in cybersecurity, serving as a tool to confuse attackers by mimicking real network behaviour. This adds an extra layer of protection, making it harder for attackers to breach the system.
6. **Scope for Future Work**: While the results are promising, future work could focus on improving the model's architecture to generate even better decoy data. Additionally, real-time data generation, combined with an interactive interface, could make the solution more practical for dynamic network environments.

In summary, this work highlights the successful use of GANs to generate realistic decoy network traffic, offering a new defense mechanism in cybersecurity. By applying machine learning, this approach lays the foundation for innovative strategies to protect against evolving cyber threats.

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