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Master in Computer Engineering

GAN for Network Traffic Generation

using ZEEK IDS

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Introduction

Packet caputere dataset can be used for evaluating network-based detection-systems, also known as NIDS. In this reasearch we want to generate new packet capture dataset that are realistic.

The approach used is based on *Generative Adversial Networks (GANs)* which achieve good results for image generation. The main problem here is that work very well with continuos attributes, and they can process only them. However, packet capture data contain categorical attributes such IP addresses or port numbers. Exploiting this characteristic of the data that we use, we can implement an approach for generating packet-capture data to transform them into continuos values.

Once the data is generated, there is a testing phase that also include the usage of a real NIDS to verify if they are corretly generated and identified. In that phase we use **ZEEK** that is an open source network analysis framework, but in our scope we use it mainly as a Network Intrusion Detection System.

In the following pages we will discuss all the detail and the motivation for all the deciosion that has been made.

CHAPTER 1 | ZEEK

As mentioned before the choosen tool for testing the data generated is ZEEK [1]. This tool ha many functionalities but the one that we used is the Network Intrusion Detection System. ZEEK is not only that, in fact it is a passive, open-source network traffic analyzer. That means it supports a wide range of traffic analysis tasks beyond the security domain, including performance measurement and troubleshooting. Many people use it as a Network Security Monitor or NSM, that is the collection and analysis of security informations to discover presence of hints and facts about an intrusion in the network of a company.

The usage of ZEEK aims to get an extensive set of logs, describing the network activity. These logs often includes a comprehensive record of every connection seen on the wire and an application-layer transcript. For example theese can include HTTP session, with URIs and all sort of usefull information about the connections and the general browsing activity.

By default, ZEEK uses a JSON log formatted file or a file well-structured and tab-separated: in that way the informations collected can easily be used for further analysis or post processing using external software. A common way to store these data is in an external database or SIEM, so users can consume, store, process and present data for quering.

In addition to the logs, ZEEK has build-in functionalities for a range of analysis and detection tasks, for example: extractiong files from HTTP session, detecting malware using external registers, reporting vulnerabilities seen on the network, detecting bruteforce for SSH or validating SSL certificates.

This tool is also a customizable and extensible platform for traffic analysis. In fact it provides the users a domain-specific, Turing-complete scripting language for expressing analysis tasks. The ZEEK language comes with a large set of pre-build functionalities, like a standard library, and users can write custome code. Indeed, all of defalult analyses, including logging, are done vie scripts; no specific analysis is hard-coded in the system.

ZEEK can run also on low budget hardware and hence can be a low-cost alternative to expensive propetary solutions. In many ways this software exceeds the capabilities of other network monitoring tools, that remain limited to a small set of hard-coded tasks. ZEEK is not a signature-based Intrusion Detection System (IDS); while supporting this functionality, the scripting language facilitates a broader spectrum of different approaches to find malicious activities. These include semantic misuse detection, anamaly detection and behavioral analysis.

This tool also support scalable load-balancing so it can be used for high-performance scenarios. Large site and organizations can use ZEEK Clusters, in which high-speed front end load balancer distributes the traffic across an appropiate number of back end PCs, running dedicated ZEEK instances on individual traffic slices.
A Central Management System is used to coorinate the process, synchronizing state across the back ends and providing the operators with a central management interface for configuration and get aggregates logs. In that way ZEEK can be used in both single and multi systems setups.

In conclusion ZEEK is optimized for interpreting network traffic and generate logs, based on the traffic analyzed. It's not optimized for byte mathcing and users seeking signature detection approaches, like Intrusion Detection Systems do, and is not a protocol analyzer, seeking for depict every element of traffic at the frame level like Wireshark do. Zeek is in the middle seeking to get high fidelity network logs, generating better understanding of network traffic and usage do. Zeek is in the middle seeking to get high fidelity network logs, generating better understanding of network traffic and usage.

1.1 | Architecture

In this part we describe, at a very high leve, the ZEEK architecture. ZEEK is composed by various layers. The *event engine* (or core) reduces the incoming packet steam into a series of higher-level *events*. These events reflect the network activity in policy-neutral terms, they describe what has been seen but not why or if it is important.

For example, an HTTP request turns into an *http_request* event that carries the usefull informations, like the IP addresses and ports, URI, HTTP versions and values. The event however does not convey any further interpretations, such as if the URI corresponds to a malware site.

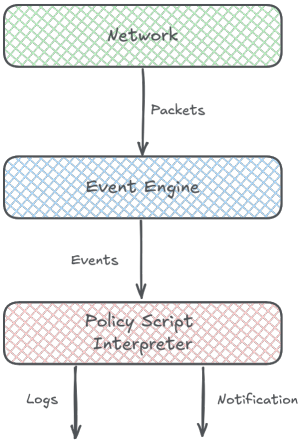


Figure 1.1: Architecture of ZEEK

The event engine component comprises a number of subcomponents, including in particular the packet processing pipeline consisting of: input sources, packet analysis, session analysis and file analysis. Input sources incest incoming network traffic from network interfaces. Packet analysis process lower-level protocols, starting all the way down at the link layer. Session analysis handles application-layer protocols, such as HTTP, FTP, and so on. File analysis dissects the content of files transferred over sessions. The event engine provides a plugin architecture for adding any of thes from outside of the core ZEEK code base, allowing to expand ZEEK's capabilities as needed.

Semantics related to the events are derived by the second main layer: the *script interpreter*. This executes a set of *event handlers* written in ZEEK language. These scripts can express a site's security policy, such as what actions to take when the monitor detects different types of activity.

More generally scripts can derive any properties and statistics from the traffic. All ZEEK outputs comes from scripts included in the distribution. The language can generate real-time alerts and execute external programs on demand. One might use this functionality to trigger an active response for attack.

With this we had introduced what ZEEK is and briefly how it works.

CHAPTER 2 | Input Data

To make new data similar from some existing ones, we need a dataset of how those data needs to look like. For this reason we describe di input data, from which we can create new examples. The inital data needs to be transformed in some way, so it can be given as an input of our GAN.

The composition of our dataset is a pcap file. This kind of files contain packet data of a network and are ofen used to analyze the network characteristics and detect if there're anomalies and intrusions. Since this kind of data is difficult to manage, even if it's well formatted, a first step is to convert the data as a csv dataset.

In this way we can easily manage the data before giving them to the network and viewing the final results in a simpler way. The pcap file is something like the following: while the output of the conversion of the pcap into the csv is a dataset like:

2.1 | Data Conversion

To convert the pcap file into the csv, and viceversa we have created the following script that aims to do this kind of transofrmations. The foundamental informations are extracted using Scapy [2], a python library used to extract data from packets saved into a pcap file. The main information that we need are:

- the packet number
- the protocol used
- the timestamp
- the source ip and port
- the destination ip and port
- the flag if tcp protocol is used

from the script we extract those infos from the pcap and store them into the final csv, for each packet into the file.

Once adjusted the data source, we can continue developing the core of the project: the GAN that generates new data.

CHAPTER 3 The GAN

Developing the GAN poses many question, but the first and most important one is the fact that GANs work better with continuos input attributes and the data present in our dataset it is not of this kind. For this we have to apply some tricks so that our data can be given as an input of the Neural Network.

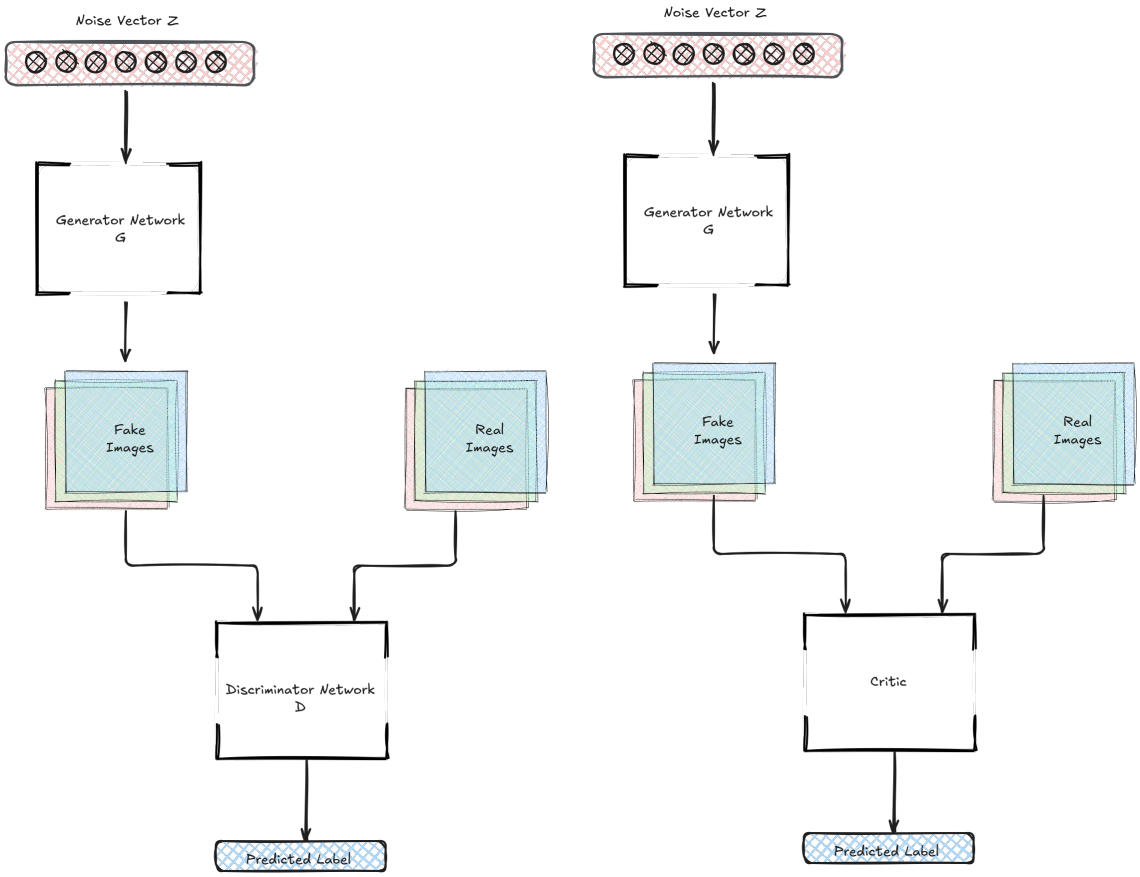
Before diving deeper into the implementation of this process it is necessary to discuss what a GAN is. A GAN o Generative Adversarial Network is a Neural Network used to generate synthetic data by learingn from a given set of input data. GANs are made of two networks, a generator G and a discriminator D. The generator is trained to generate synthetic data from noise. The goal of the discriminator is to distinguish generated data from the real word data. The generator is trained iteratively until the generator is able to fool the discriminator. GANs are really good at generating images, but they have achieved good result also in text generation or molecule generation.

Discriminative models aim to classify objects into predefined classes. In contrast to discriminative models, generative ones are used to generate data like the network traffic. Many generative models build on likelihood maximization for a parametric probability distribution. The generator tries to mimic sample from the data distribution, while the discriminator has to differentiate the real and the generated samples. Both networks are trained iteratively until the discriminator can't distinguish real and generated samples. The generator is never updated with real samples. The generator is fed with an input vector of noise z. So it is trained using only the discriminator's gradient through backpropagation. Therefore it is less likely to overfit the generato by memorizing and reproduct real samples. The vanilla GANs requires the visible units to be differentiable, which is not the case for categorical attributes like IPs in the data used. WGANs [3] [4], are capable of modelling discrete distributions over a continuos latent space and have other advantages. The main difference is that WGANs uses the Earth Mover (EM) distance as a value function replacing the classifying discriminator network with a *critic* network estimating the distance. To solve the problem of non-convergence in the GANs, it could be useful to apply Two Time-Scale Update (TTUR) for training GANs with arbitrary functions. For this reason we have choosen to utilize WGANs with TTUR.

3.1 Preprocessing

Since the packet capture network traffic that we use as input is made of by both categorical and continuous data, we need a way to transform the categorical data into continuous ones. There are various methods to do so, one of them is tho simply treat the attributes like IP and ports as numerical values. The second method could be to create binary attributes from categorical ones. The last method uses IP2Vec to learna meaningful vector rapresentation of the categorical attributes.

Since the first two methods are less precise, but are more simple to implement, it has been choosen to implement directly the third method even if it is more complex. This due to the fact of attempting to obtain a better approximation of the input data, and this method works better than the other two.



(a) Classic GAN architecture

(b) Architecture of a WGAN

3.2 | IP2Vec

IP2Vec [5] is a work inspired by Word2Vec and aims to transform IP addresses into a continuous feature space $\mathbb{R}^m$ such that standard similarity measure can be applied. To do that we can extract the available context information from the network traffic. For example the *IP addresses* that appear in similar contexts will be close to each other in the feature space $\mathbb{R}^m$. This means that similar context imply the fact that the devices associated to thes IPs establish similar connections.

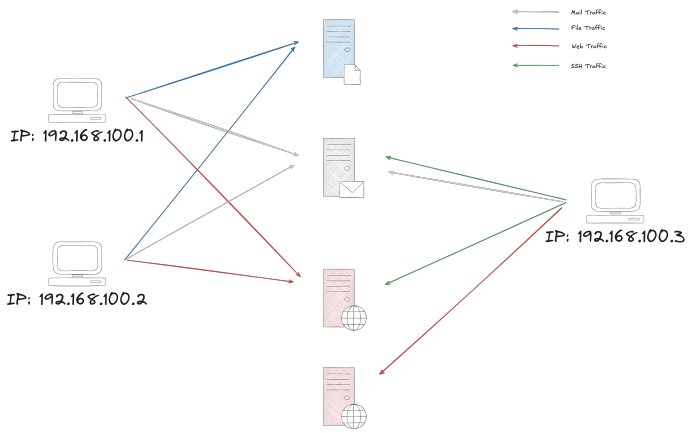


Figure 3.2: Example of connections

In the figure we can see the idea of IP2Vec. The arrows denote network connections from the IPs and the different colors indicate different services. From the image we can tderive that the conection made by the devices on the left side are more similar that the ones made by, for example, the host

192.168.100.2 and 192.168.100.3. This due to the fact that the first couple use the sama kind of connection referred to the same targets and services.

3.2.1 Model

IP2Vec is based on a fully connected neural network with a single hidden layer.

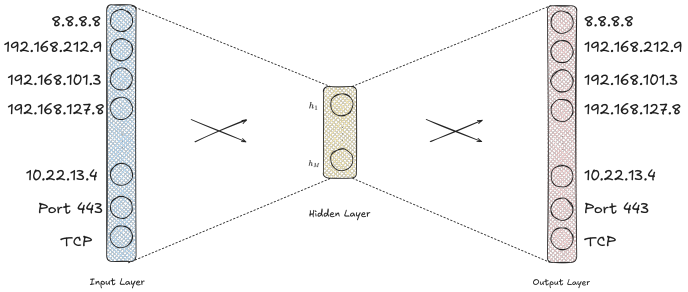


Figure 3.3: Neural Network representation

The features that are extracted from the network traffic consitute the input of the network. The features consists of the IP addresses, destination ports and trasport protocols and contribute to create the vocabulary that contain all of the features that can be seen in the dataset. Since we cannot have categorical attributes, the vocabulary is represented as a one-hot vector that has the length of the size of the vocabulary.

Each neuron in the input and output is then assigned to a specific value of the vocabulary. The output layer uses a softmax classifier that indicates the probability of each value of the vocabulary that it appears in the same context as the input given. The classifier normilizes the output such that the sum is 1.

3.2.2 Train

In the training process the neural network is fed with the input value and it tries to predict the probability of the other values from the vocabulary. For the trining samples the probability of the concrete output value is 1 and 0 for all the others. The network uses back-prpagation for learning.

With that, we conclude the digression on how the input data is transformed in a way that can be fed to the GAN. Since the data generated is then reproduced as an embedding vector it needs also to be converted in a format similar to the dataset, for that we have used a script that implement that feature

CHAPTER

4 Results

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