

A Graph Neural Network Approach for Scalable and Dynamic IP Similarity in Enterprise Networks

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Abstract—Measuring similarity between IP addresses is an important task in the daily operations of any enterprise network. Applications that depend on an IP similarity measure include measuring correlation between security alerts, building baselines for behavioral modelling, debugging network failures and tracking persistent attacks. However, IPs do not have a natural similarity measure by definition. Deep Learning architectures are a promising solution here since they are able to learn numerical representations for IPs directly from data, allowing various distance measures to be applied on the calculated representations. Current works have utilized Natural Language Processing (NLP) techniques for learning IP embeddings. However, these approaches have no systematic way to handle out-of-vocabulary (OOV) IPs not seen during training. In this paper, we propose a novel approach for IP embedding using an adapted graph neural network (GNN) architecture. This approach has the advantages of working on the raw data, scalability and, most importantly, induction, i.e. the ability to measure similarity between previously unseen IPs. Using data from an enterprise network, our approach is able to identify high similarities between local DNS servers and root DNS servers even though some of these machines are never encountered during the training phase.

I. INTRODUCTION

The problem of measuring how similar a group of machines are, denoted with their IPs, is an important aspect in a large number of network operations and security analysis tasks. In the security context, malicious behavior such as an Advanced Persistent Attack (APT) typically affects multiple machines at a time [1] – in the initial phases the adversary is looking for exploits in the edge network assets, while later in the attack after successfully infiltrating the network the adversary is spreading internally. Alert correlation is of crucial importance in detecting APTs, where individual alerts are not necessarily an indication of an actual attack. Instead a correlated group of such alerts following a proper attack plan is a significantly better indication of malicious behavior [2]. Since an alert is typically defined through its attributes, such as IP addresses, port numbers, ... etc, the problem of alert similarity entails the one of IP similarity, where two alerts are more similar if the IPs involved in both alerts are also similar. The problem under study here, IP similarity, is then a subset of the larger problem of general alert similarity.

Once a security alert is triggered, it is presented to the analyst for further investigation, following which the analyst may choose to tag the alert as false-positive. The problem

of the high rate of false-positives in security analytics and behavioral modelling is a well-documented one [3]. One approach here is to ask the analyst for feedback on a small set of alerts, and use this feedback to better label the rest of the larger group of alerts through alert similarity, forming an active-learning loop [4]. This again leads to the question of alert similarity, and consequently to that of IP similarity.

User Entity Behavior Analytics (UEBA) [5] and Network behavior anomaly detection (NBAD) leverage statistical approaches for threat detection in modern enterprise networks. The most common approach here is to build behavior baselines from historical traffic data and evaluate new incoming data against these baselines. An alert is then triggered if the new traffic deviates significantly from the established baselines. However, this approach suffers greatly with new machines and sparse traffic. For example, consider a load-balanced system where one server is capable of handling most of the requests while a backup server is idle during the majority of time. A UEBA system may trigger an excessive number of alerts for this idle server when the load increases and it has to handle more traffic. One solution is to use not only the data for the machine under study but also the data from similar machines, in order to build a more robust baseline. In this case, the question of similarity between machines is of significant importance.

A. Related Work

The problem of distance measures between IP addresses has been extensively studied in the literature, particularly in security applications. One of the earliest works is [6], where the hierarchy of IP addresses is used to measure their pairwise distances depending on how far they are in the hierarchy tree. This approach has been extended in [7]. Both approaches however have the drawback of being manually designed and not granular enough beyond the main divisions in the tree, such as public versus private IPs.

Another line of work uses the bit representation of IPs and measures distances based on the length of the longest common prefix [8]. This approach has been utilized to group alerts together into an attack graph if the distances between them is below a certain threshold. However, this approach suffers from putting too much faith in IP allocation, where successive IPs are assumed to be assigned to the most similar machines. With the migration to the cloud and the dynamic scaling of

enterprise networks, these assumption are becoming out-dated. Moreover, this approach is not designed to handle similarity between public IPs.

Driven by the limitations of static, manually-designed distance measures, and inspired by recent advances in NLP and word embeddings, IP2vec [9] was proposed as an extension of the popular word2vec [10] paradigm to the networking domain. The idea behind the approach is to treat network logs as the equivalent of a text corpus in NLP, and entries in the log message, such as IPs and port numbers, as the equivalent of words. Finally, train a neural network on this data and use its hidden layer as the embedding of the network entities of interest. These entities include IPs, ports and network protocols. This approach does not generate similarity per se, instead it generates a numerical representation for each network entity. Various distance functions can be applied on the given numerical representations to get the required similarity. This approach has the advantage of learning representation directly from data without the need for manually-designed measures, rendering it more practical and flexible. Recently, this approach has been applied to the detection of persistent attacks in enterprise networks with promising results [11].

B. Proposed Methodology

In this paper, we take this approach one step further by leveraging graph neural networks (GNNs) to generate an embedding for the nodes of the network communication graph, where each node is a distinct IP. Our motivation behind this approach is as follows:

- Network data represents a graph, in particular the flow/connection logs describe the communication graph between the different entities in the network. This makes GNNs a natural choice to get a representation of the graph and its nodes.
- Out-of-vocabulary (OOV) problem: this is a well-known problem in NLP concerned with how to handle new words during testing which were not seen during training [12]. This problem is more challenging in our case since networking data is much more dynamic than text data, especially in cloud networking. New IPs show up all the time, whether due to new machines joining the network, new external servers that users access, or dynamically allocating IPs in the network. The ability to generate a representation of previously unseen IPs is a crucial feature in a network embedding model. NLP-based approaches fall short here, while a large training text corpus is usually enough to see almost all relevant words, this is not the case with networks data due to the large number of IPs ($\sim 2^{32}$ for IPv4 and $\sim 2^{128}$ for IPv6). Moreover, these enormous numbers of potential IPs hinder the feasibility of building a model that can handle all possible values. The NLP field has some approaches to handle the OOV issue, none of which are applicable to our problem. One common solution is to generate character embeddings, single or few characters, and build a word embedding from the embeddings of its composing characters [13].

However, IP addresses do not have the same compositional nature as words. While changing a single character is unlikely to change its word's meaning, two IPs with only one different bit can belong to two machines with completely different nature. Another approach to address OOV is to have a singular representation for all unseen words. Clearly, this solution is not applicable here. While in NLP tasks the size of OOV is small, in networking due to the huge number of IPs, the number of IPs encountered in any realistic training set is much smaller than the total number of IPs in the internet, and the size of OOV is actually quite significant.

The rest of the paper is organized as follows: Section II provides an overview of graph neural networks. Both the system and neural network architectures are discussed in Section III. In Section IV we show the results from a real network dataset. The paper is concluded in Section V.

II. OVERVIEW OF GRAPH NEURAL NETWORKS

Graph neural networks comprise a special class of neural networks designed to handle data in a non-Euclidean vector space in the form of a graph [14] [15]. The goal is to leverage the benefits of deep learning methods, such as distributed representations and end-to-end learning [16], for application domains in which the data does not fit into the more popular paradigms of convolutional or recurrent neural networks (CNNs, RNNs). Examples of this non-Euclidean data are chemical molecules, citation networks, user-product interaction in e-commerce, and, in our case, communication networks.

One of the more popular problems studied in GNNs is known as network embedding, where the goal is to generate low-dimensional vector representation for the graph nodes in line with the graph topology and the node information content [17]. These representations, also referred to as embeddings, are then used for various tasks such as node classification, clustering, and in our case, measuring similarity between nodes using their vector representation.

GNNs can be classified into two broad families [14]: message-passing convolutional GNNs and Weisfeiler-Lehman GNNs. Message-passing GNNs update a node representation using the representations of its neighbors, through variations of the basic formula:

$$h_i^{l+1} = f \left(W_1^l h_i^l + \sum_{j \in \mathcal{N}_i} W_2^l h_j^l \right) \quad (1)$$

where h_i^l is the representation of node i at layer l , $f(\cdot)$ is a non-linear mapping such as ReLU, W 's are learnable weight tensors and \mathcal{N}_i is the set of neighbors for node i .

One of the major advantages of message-passing GNNs is their inductive nature. A GNN is called inductive if, during the test phase, it can generate a representation for a node it has not seen before during the training phase. This is mainly due to the parameter sharing between all nodes and the message passing operation itself [18]. This inductive nature is a key

feature that we believe gives GNN the edge over NLP-like approaches for the task of IP embedding.

In summary, our design goals for GNNs in the embedding of network IP addresses are:

- Inductive vs transductive: inductive approaches can embed unseen nodes, a feature we need for constantly changing networks.
- Edge attributes: compared to other application domains, edge information such as protocol, byte count, ... etc are particularly important for our use-case.
- Anomaly detection: an auto-encoder based loss function is useful here as the GNN would not only provide the embedding but also an anomaly signal if the communication network snapshot is significantly different from the training data.

III. SYSTEM DESCRIPTION

A. Architecture

The input data to our system is the set of network logs from the Bro/Zeek monitoring tool¹. These logs are pre-processed for any data enrichment/cleaning and then used to build the communication graph of the network. An offline training step uses a large historic dataset to train the GNN and save the trained model. During real-time operation, a new batch of data is applied to the model every fixed interval, 10 minutes for example, and the inference operation of the GNN provides the embeddings for the IPs seen during the interval as well as an anomaly signal if needed. The offline training operation can be periodically repeated as deemed necessary. Note that due to the inductive nature of the model, we can do the training on one network and deploy the model on as many networks as desired, resulting in more deployment flexibility.

B. Mathematical Model

Our model is an extension of the Residual Gated Graph Convolution model proposed in [19], and shown in [14] to be one of the best performing GNN models on a variety of tasks.

1) *Data Format*: The input data to our system comes from Bro/Zeek conn.log files. Table I has a list of the fields we use in our experiments.

TABLE I
FIELDS USED FROM ZEEK CONN.LOG FILE

Group	Fields
IP information	sourceIP, destinationIP
Port Information	sourcePort, destinationPort
Protocol Information	protocolService
Numerical Traffic Features	responseBytes, requestBytes, duration, bytes, responsePackets, requestPackets, responseIPBytes, requestIPBytes

¹<https://zeek.org/>

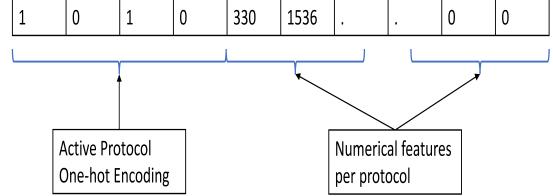


Fig. 1. Edge input feature vector

Due to the incredibly high rate of new connections in any real world network, we group connections together into a single graph for a fixed interval, 10 minutes for example. In particular, the data is first grouped by *sourceIP*, *destinationIP*, *protocolService* and the *sum* aggregation operation is applied on the numerical features such as *responseBytes*, *requestBytes*, *duration*...etc. This grouping for small intervals strikes a nice balance between unrealistically running a new inference for every change in the graph, i.e. every new connection in the network, and building a static graph for large intervals.

The structure of the graph is then as follows:

- Node: each node represents an IP.
- Edge: There is at most one edge connection between two nodes if at least one connection happened between them using any protocol.
- Node Features: we do not have any node features.
- Edge Features: each edge has a feature vector of the following format: the first part of the feature vector is a one-hot encoding of all the protocols seen between the source and destination nodes, and the rest is the concatenation of the aggregated numerical features for all protocols under study, as shown in Fig. 1.

Since each node represents an IP, and in most deployments we do not have access to end-point data, there are no node features per se. This is a stark departure from existing models and datasets, where node features are the most important part of the data. Instead, in networking applications, almost all data is contained in the edge features, such as protocol information and traffic volume.

2) *GNN Input Layer with Edge Features Only*: Since in our graph the nodes are feature-less, we propose a new input layer that works solely on the edge features and can use them to generate preliminary node feature vectors.

The input layer, shown in Fig. 2, functions as follows:

$$h_i^1 = \text{RELU} \left(BN \left(\sum_{j \in N_i} e_{ij}^1 \odot V^0 e_{ij}^0 \right) \right) \quad (2)$$

where W^0 is a trainable weight matrix, BN stands for batch normalization, \odot is the Hadamard product, and the edge gates

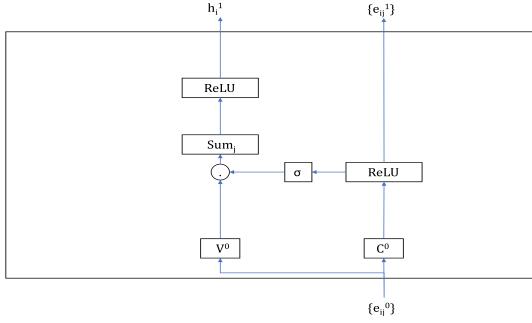


Fig. 2. GNN Input Layer with Edge Features Only

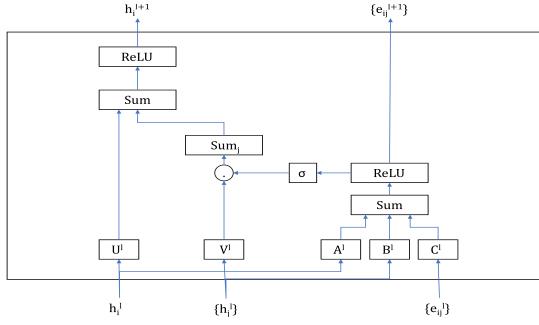


Fig. 3. GatedGCN Convolutional Layer

e_{ij}^1 are defined as

$$e_{ij}^1 = \frac{\sigma(\hat{e}_{ij}^1)}{\sum_{j' \in N_i} \sigma(\hat{e}_{ij'}^1) + \epsilon} \quad (3)$$

$$\hat{e}_{ij}^1 = e_{ij}^0 + \text{RELU}\left(BN\left(C^0 e_{ij}^0\right)\right)$$

3) *GatedGCN Convolutional Layers*: Following the input layer, the other layers are the same as the convolutional layers in the original GatedGCN model in [19]. These layers, shown in Fig. 3, take the form

$$h_i^{l+1} = h_i^l + \text{RELU}\left(BN\left(U^l h_i^l + \sum_{j \in N_i} e_{ij}^l \odot V^l h_j^l\right)\right) \quad (4)$$

$$e_{ij}^l = \frac{\sigma(\hat{e}_{ij}^l)}{\sum_{j' \in N_i} \sigma(\hat{e}_{ij'}^l) + \epsilon}$$

$$\hat{e}_{ij}^l = \hat{e}_{ij}^{l-1} + \text{RELU}\left(BN\left(A^l h_i^{l-1} + B^l h_j^{l-1} + C^l \hat{e}_{ij}^{l-1}\right)\right)$$

where U^l, V^l are trainable weight matrices.

In both types of layers, the edge gates e_{ij}^l can be seen as a soft-attention mechanism [14].

4) *Loss Function*: Our loss function is composed of two parts:

- Edge Feature Reconstruction: this is main part of the loss function and represents the auto-encoder learning objective. The goal here is to reconstruct the edge features from the low dimension representation as follows:

$$\text{loss}_{AE} = \lambda_{AE} \text{BinaryCrossEntropy}\left(e_{ij}^0, e_{ij}^d\right) \quad (5)$$

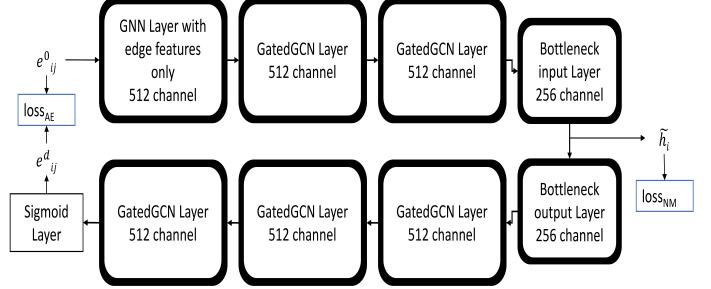


Fig. 4. GNN Model

where e_{ij}^0 are the input edge features, e_{ij}^d are the feature representations from the last layer of the decoder and λ_{AE} is the weight of the reconstruction loss.

- Neighborhood Embedding Match: similar to other graph auto-encoder approaches [20], we would like the embeddings of neighboring nodes to be similar:

$$\text{loss}_{NM} = -\lambda_{NM} \sum_{i=1}^N \sum_{j \in N_i} \log\left(\frac{1}{1 + \exp(-\tilde{h}_i^T \tilde{h}_j)}\right) \quad (6)$$

where \tilde{h}_i, \tilde{h}_j are the embeddings of nodes i, j respectively, and λ_{NM} is the weight of the neighborhood match loss.

The total loss is simply the sum of both loss functions $\text{loss} = \text{loss}_{AE} + \text{loss}_{NM}$.

The complete GNN model is shown in Fig. 4. The sparsity of the input edge feature vectors proved to be a consistent challenge for the stability and convergence of the GNN learning process. To handle this issue, we have found it best to normalize the input features, use a *Sigmoid* layer as the output of the decoder and *BinaryCrossEntropy*(.,.) as the loss function between the two.

IV. RESULTS

In this paper, we use a private dataset from a medium-sized enterprise network. This network has around 50 users using primarily windows machines, and a few internal servers. The traffic sensor is located such that it can capture both the traffic between internal hosts as well as between internal and external hosts, so-called east-west traffic and north-south traffic.

We conduct two main experiments to judge the ability of our model to measure similarity between new and previously observed nodes. In particular, given a set of IPs that we know to belong to machines of similar functionality, we remove a subset during the training phase and only introduce them back during the testing phase. We do so by removing all conn logs where either the *sourceIP* or the *destinationIP* is the part of the subset to be removed. We then test the model's ability to produce high similarity between the whole set of such IPs, not only the ones seen during training. We conduct this experiment using two sets of IPs:

- Local DNS servers: the network under study has two local DNS servers, 192.168.2.15 and 192.168.2.19. We remove 192.168.2.19 during training.

- Root DNS servers: these servers are the highest in the hierarchy of the internet DNS servers². Their IPs are 198.41.0.4, 199.9.14.201, 192.33.4.12, 199.7.91.13, 192.203.230.10, 192.5.5.241, 192.112.36.4, 198.97.190.53, 192.36.148.17, 192.58.128.30, 193.0.14.129, 199.7.83.42, 202.12.27.33. We remove the last four IPs during training time and measure their similarity with the first nine IPs during test time.

In all our experiments we adopt the cosine similarity measure:

$$d(\tilde{h}_i, \tilde{h}_j) = \frac{\tilde{h}_i^T \tilde{h}_j}{\|\tilde{h}_i\| \cdot \|\tilde{h}_j\|} \quad (7)$$

We also conduct all experiments using both $loss_{AE}$ and $loss_{AE} + loss_{NM}$ as the loss, with $\lambda_{AE} = 1.0$, $\lambda_{NM} = 0.01$.

In Table II, we show the similarity between the two IPs, 192.168.2.15 and 192.168.2.19 on the test graphs. Except for the first row, the similarity between these two IPs quickly reaches very high values, indicating the ability of the model to recognize the similar behavior even though only one IP was seen before. We posit that for shorted periods, e.g. 10 minutes, the amount of traffic seen might not be representative enough of the typical behavior of the machine and hence one model produced low similarity between the two IPs in this case.

In Table III we show a similar set of results but for the root DNS servers. Similarity is averaged across all possible pairs when the first IP is one of the 9 root IPs seen during both training and testing while the second IP belongs to the set of the 4 root IPs seen only during testing. The same observation holds here that the model was able to recognize the similarity between these public IPs due to their similar functionality. We also see high similarity here even for the shorter period of 10 minutes. We explain that as public DNS servers would only receive one kind of traffic, that is DNS queries. On the other hand, since we have more visibility into the traffic between the local machines, including local DNS servers, it takes a longer interval to see the dominant traffic pattern for local machines. We would like to note that although we have a relatively high number of test graphs, the inference passes are independent across each graph. In other words, the model does not need to see a large number of graphs including the IP(s) under study, in fact, once the model is trained, it can generate a high-quality embedding for an IP from a single test graph.

We also provide visualizations of some interesting clusters of similar IPs. Fig. 5 shows the visualizations of all IPs in the network during a single interval with some interesting clusters highlighted, these clusters are zoomed on in the figures to follow. Fig. 6 has a cluster including the root DNS IPs discussed before. Fig. 7 has the broadcast IP 255.255.255.255, and all the other IPv6 addresses are multicast IPs. In Fig. 8, all the IPs of the form 17.* belong to Apple. In all four figures, t-SNE [21] is used for the 2-dimensional visualization.

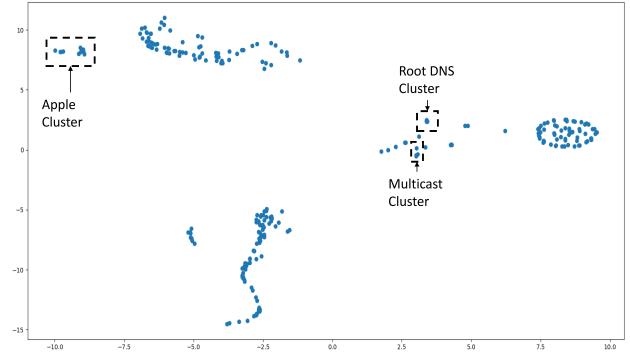


Fig. 5. t-SNE visualization of all IPs with highlighted clusters

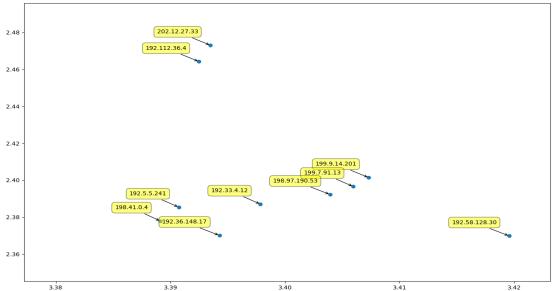


Fig. 6. t-SNE visualization of Root DNS Cluster

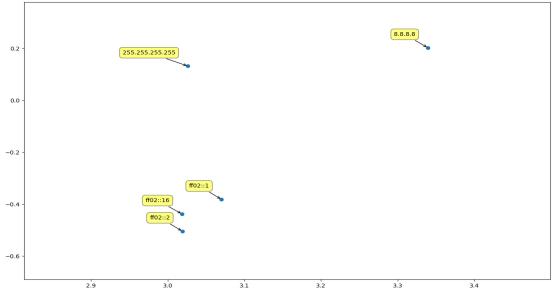


Fig. 7. t-SNE visualization of Broadcast and Multicast Cluster

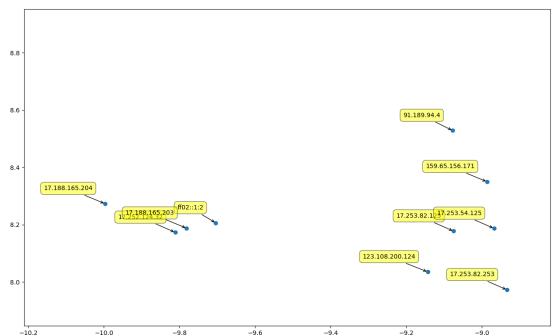


Fig. 8. t-SNE visualization of Apple Cluster

V. CONCLUSION AND FUTURE WORK

In this paper, we introduced the first study on applying GNNs for the embedding of network assets, represented as

²https://en.wikipedia.org/wiki/Root_name_server#Root_server_addresses

TABLE II
SIMILARITY BETWEEN TWO LOCAL DNS SERVERS WHEN ONLY ONE IS SEEN DURING TRAINING

Graph Interval Length	$loss_{AE}$ Similarity	$loss_{AE} + loss_{NM}$ Similarity	Number of Test Graphs
10 minutes	0.7060738 ± 0.34426507	0.9862463 ± 0.01696037	207
30 minutes	0.9743041 ± 0.04809975	0.9869821 ± 0.01701941	70
60 minutes	0.9647852 ± 0.06598776	0.9906003 ± 0.01601414	35
120 minutes	$0.9880788 \pm 0.030548556$	0.9803449 ± 0.05673271	18

TABLE III
AVERAGE SIMILARITY BETWEEN ROOT DNS SERVERS

Graph Interval Length	$loss_{AE}$ Similarity	$loss_{AE} + loss_{NM}$ Similarity	Number of Test Graphs
10 minutes	0.9654844 ± 0.04811225	0.9918937 ± 0.00860384	207
30 minutes	0.9791588 ± 0.03466465	0.9879824 ± 0.01978309	70
60 minutes	0.9768600 ± 0.04310611	0.9870570 ± 0.01964757	35
120 minutes	0.9930404 ± 0.01426881	0.9593274 ± 0.09711087	18

IPs. We identified a few challenges that render this problem uniquely different from both NLP-based network embedding and the more common use-cases of GNNs. These challenges revolve mainly around the inductive nature of a model being significantly more important compared to text data, and the lack of node features in typical deployments of such a model. We then introduced a new input layer to handle our data, and the necessary output layer and loss function to stabilize the training process. The outcome is an efficient embedding for each asset in the network incorporating its own as well as its neighbors traffic behavior. Our results show that the model is able to properly represent similar IPs even though only a subset of those IPs has been seen before during the training phase. The model is also able to highlight interesting IP clusters, such DNS servers, broadcast/multicast IPs and Apple IPs.

An extension to our approach is to introduce node features in the system. These node features will have to come from end-point data, such as Windows event log. The model can then learn better embeddings representing both the end-point and the network behavior of each asset in the network. We also plan to test our approach on larger datasets with multiple IP subnets.

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