

**Detecting Internet-Scale NATs for IoT Devices Based on Tri-Net**

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**Abstract.** Due to the lack of available labeled Network Address Trans- lation (NAT) samples, it is still diﬃcult to actively detect the large-scale NATs on the Internet. In this paper, we propose an novel method to identify NATs for online Internet of Things (IoT) devices based on Tri- net (a semi-supervised deep neural network). By learning the features on three layers (network, transport and application layer) in the small labeled data set (with thousands of instances), the Tri-net can automat- ically identify millions of online NATs. We evaluate this approach on the real-world dataset with more than 8 million online IoT devices, and the performance shows the precision and recall can be both up to 92%. Moreover, we found 2*,*511*,* 499 IoT devices connecting to the Internet via NAT, which account for one-third of the total. To our knowledge, this is the ﬁrst successful attempt to automatically identify Internet-scale NATs.

**Keywords:** NAT detecting *·* IoT devices *·* Tri-net

# Introduction

The number of online IoT devices (e.g., IP camera, wireless router, etc.) has grown explosively. Meanwhile, limited public IPv4 addresses can not meet the needs of those devices connecting on the Internet. NAT has become the ideal solution that allows multiple devices sharing one public IP address or provid- ing Internet-wide services via port mapping. However, NAT also undoubtedly bring some security issues to the online IoT devices: (1) NAT prevents the empirical investigation into counting the actual number of vulnerable devices in cyberspace. (2) Unauthorized NAT devices provide the convenience for the mali- cious code infection. Therefore, it is necessary to actively detect NAT behaviours of IoT devices in the cyberspace.

Consequently, NAT detection has become a typical and valuable research issue. Most studies focused on passive approaches on traﬃc traces [[2](#_bookmark14), [8](#_bookmark20), [11](#_bookmark23), [13](#_bookmark25)]. That is because the performance evaluation of active detecting NAT devices

*Q*c Springer Nature Switzerland AG 2020

D. Yu et al. (Eds.): WASA 2020, LNCS 12384, pp. 602–614, 2020.

<https://doi.org/10.1007/978-3-030-59016-1_50>

is more uncontrollable and uncertain than passive measurement. As a result, the current research on active NAT detection approaches have been slightly fewer [[9](#_bookmark21), [11](#_bookmark23)]. Moreover, there are still no usable approaches to identify NAT for the large-scale targets, especially for the online IoT devices in the complex cyberspace.

**Motivation:** In this paper, we aim to quantify the above assumption, and con- duct an comprehensive Internet-scale study on active NAT detection toward online IoT devices with multiple features on network, transport, and application layers based on Deep Neural Network (DNN). Speciﬁcally, we try to answer the following questions: (1) *How many NATs are used by online IoT devices across IPv4 address space?* (2) *How many IoT devices connected to the Internet via their public IP addresses?* (3) *What is the distribution of geography, type, and protocol of those NATs?*

**Challenges:** To achieve this end, we need to address the three main chal- lenges. One the unstable features for active detecting NATs has its limitation. For instance, IP identiﬁcation (IP ID) and time-to-live (TTL) can be modiﬁed or forged. More importantly, due to the large heterogeneity in IoT devices, not all features on each layer can be obtained on the Internet. Besides, inadequacy features cause the lackness of labeled NAT samples for training the applicable machine learning modules. These main reasons make the active NAT detection seems to be impossible in the real world.

**Method:** To address these challenges, we design and implement an approach to identify NATs for online IoT devices in IPv4 space automatically. The workﬂow of our approach consists of three steps. First, we pre-label a small part of the dataset and extract the relatively features on network, transport, and applica- tion layers. Second, we train the modules of Tri-net by automatically feature learning and three pseudo-labels on diverse layers predicting. Third, we deter- mine whether it is a NAT or straight-connecting device based on the trained Tri-net and the enlarged labeled dataset.

**Results:** To evaluate the performance, we implement our approach to the real Internet-wide public data. The data set contains 8,644,288 online IoT devices with four categories (routing, monitor, printing, and industrial control). Among which, we identiﬁed 2,511,499 IoT devices using NAT for Internet access, which occupy 29*.*1% of the total experimental data set.

**Contributions:** Overall, we make the following desirable contributions:

* *First available online NAT detecting approach:* Combined ﬁve new features we introduced on the application layer and six typical features on the transport and network layer, our work is the ﬁrst to conduct an automatic approach that can be used to identify Internet-wide NATs of the online IoT devices.
* *High precision and recall in the real experiment:* According to the real evalua-

tion in the cyberspace, our novel approach present that the average precision and recall can both be up to 92%.

– *First investigation of NAT usage status which do not require cooperation:* We identiﬁed 2*,*511*,*499 Internet-wide IoT devices using NAT, which occupy one- third of the total number. Moreover, we analyzed the distribution from four dimensions: protocol, type, vendor, and geography.

The remainder of the paper is structured as follows. In Sect. [2](#_bookmark0), we discuss the related works. In Sect. [3](#_bookmark1) and [4](#_bookmark3), we present the features and detailed approach, followed by the experimental results in Sect. [5](#_bookmark5). We discuss the future work and conclude the paper in Sect. [6](#_bookmark12).

# Related Work

Previous studies on of detecting NAT devices or identify behavior mainly focused on passive measurement [[1](#_bookmark13), [2](#_bookmark14), [8](#_bookmark20), [10](#_bookmark22), [12](#_bookmark24)–[14](#_bookmark26), [17](#_bookmark29)]. Features (*e.g.*, IP ID [[2](#_bookmark14)], TTL [[3](#_bookmark15)], the HTTP user-agent strings [[14](#_bookmark26)], *etc.*) for passive NAT detection can be easily obtain from the collecting traﬃc traces of the internal network. Thus, machine learning (ML) algorithm for passive NAT detection has not been complex. Sup- port Vector Machine (SVM), *C4.5* and Naive Bayes has been commonly used as the classiﬁers [[1](#_bookmark13), [13](#_bookmark25)]. Khatouni *et al.* comprehensively employed ten kinds of ML-based classiﬁers to achieve higher accuracy [[10](#_bookmark22)]. Sun *et al.* proposed a novel density-based clustering algorithm (*DBSCAN* ) and proved its eﬃciency [[17](#_bookmark29)].

However, these aforementioned ML algorithms made unavailable for active measurement. On one hand, it is hard to receive the traditional features from active probe data from the uncoordinated network. On the other hand, the target scale of active NAT detection is relatively larger than passive measurement. Murakami *et al.* and Ishikawa *et al.* both proposed the limited approach in their speciﬁc applications [[9](#_bookmark21), [14](#_bookmark26)]. In summary, in order to actively identify the NAT- like IoT devices in the cyberspace, new features and method need be employed.

# Preliminary Knowledge

## Features of Network Layer

All packets traveling over the network layer contain the IP header with twenty ﬁxed bytes. Among which, some classic ﬁelds are used as features for ﬁngerprint- ing OS, device types [[19](#_bookmark31)], brands and models [[18](#_bookmark30)]. In order to actively identify NAT devices based on the *<*request, response*>* packets, we choose three fea- tures on the network layer as follows: *Time to Live (ttl)*, *IP identiﬁcation (id)* and *ICMP type and code IDs (icmp)*.

The initial value *TTLinit* is set to range from 32 to 255, which is distinct from the diverse device type or OS. For instance, the *TTLinit* of D-Link IP Camera and ZyXEL wireless router are both 64 because they are using the same embedded Linux OS, and the *TTLinit* of Siemens PLC is 30 with its unique OS. Moreover, the TTL value is decremented by one as the IP datagram packet is transported at every hop. That means if the online device is directly connected

to the Internet, the value of TTL is *TTLinit* 1. For instance, Table [1](#_bookmark2) shows the TTL value of Dell Printer is 254, which means it can be concluded a non-NAT device. However, there are still some limitations of the TTL as a feature [[8](#_bookmark20)].

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IP ID ﬁeld also is useful but limited as a feature of NAT detection because it can be modiﬁed by a gateway. The unreachable message (Type: 3, Code: 3) or host unreachable message (Type: 3, Code: 1) can be used as a feature vector for NAT detection. And the feature has been proved eﬀective for Internet-scale scan on unreachable hosts [[16](#_bookmark28)].

**Table 1.** Ten features of three layer among IoT devices.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Feature | Example 1 | Example 2 | Example 3 | Example 4 |
| *ttl* | 60 | 47 | 254 | 30 |
| *id* | 61275 | 61930 | 0 | 730 |
| *icmp* | *{*3, 1*}* | *{*0, 0*}* | *{*3 ,1*}* | *{*3 ,3*}* |
| *sn & an* | - | - | - | - |
| *ws* | 4128 | 5840 | 2920 | 2048 |
| *protocol* | HTTP | RTSP | PJL Raw | Ethernet/IP |
| *port* | 80 | 554 | 9100 | 44818 |
| *banner* | Non-null | Non-null | Non-null | Non-null |
| *category* | Routing | Monitor | Printing | Industial |
| *device-type* | Router | IPcam | Printer | PLC |
| *vendor* | ZyXEL | D-Link | Dell | Siemens |
| *product* | P-330W | DCS-930 | b2360dn | S7-200 |

## Features of Transport Layer

To ensure monotonically-increasing, a NAT may rewrite the sequence number, acknowledgement number, and window size of TCP packets being forwarded into the internal realm. *TCP sequence number (sn)*, *TCP acknowledgment number (an)* and *TCP window size (ws)*. As shown in Table [1](#_bookmark2), the window size value of D-Link IP camera is 5840 and the diﬀerent value of Dell Printer is 2920. But only a part of features of transport layer can be extracted due to the inconspic- uous diﬀerences between various device types. Thus, *sn, an* and *ws* can not be independently used for NAT detection.

## Features of Application Layer

Researchers proposed Internet-wide ﬁngerprinting device type, vendor, and prod- uct based on the banners of application protocols of IoT devices such as ﬁrewalls,

SCADA and webcam [[7](#_bookmark19), [19](#_bookmark31)], which improved the basic conditions for ﬁngerprint- ing NAT devices on the Internet. Thus, we employ the following features of banners of eight general protocols, and ten particular protocols which including two monitor protocols (MP), three printing protocols (PP) and ﬁve industrial control protocols (ICP):

* *Diverse protocol categories:* Once more than two diﬀerent types of particular protocols are opened on one host, we can determine that these various proto- col services sharing one IP address by NAT device. For instance, Modbus and RTSP respectively belong to ICP and MP, which can not be simultaneously implemented on one network device. In this case, this feature is not suitable between general protocols and particular protocols because most IoT device products support multiple general protocols.
* *Standard service on well-known ports:* Some well-known ports have the oﬃ-

cial numbers for their corresponding protocol services that are assigned by IANA. However, there are still quite a number of online hosts opening their services on these well-known ports. For instance, there 660 K hosts that open HTTP services on port 23 (the oﬃcial port for Telnet) on the Internet accord- ing to our statistics. That is one kind of typical NAT behavior that is sup- ported by port mapping. Similarly, a part of unoﬃcial ports are generally designed for designative services by the IoT Manufactures.

* *Multiple standard services on unknown ports:* Part of IoT devices allow the

users to open various services on any ports with one IP address by port for- warding. For instance, Network Video Recorder (NVR) can be conﬁgured to simultaneously open RTSP services for several IP cameras on 515 (designated for a Line Printer Daemon (LPD) oﬃcial port) or 1515 of an unknown port.

* *NAT Devices:* Many IoT devices have all series or parts of products

oﬀering native NAT functions, including wireless routers, Digital Video Recorder(DVR), etc. Their dimensional features can be learnt by the neu- ral network.

* *Multiple diﬀerent device types, vendors or products:* Generally, an indepen-

dent device connects to the Internet and exposes its only TVP (type, vendor, product). Hence, if there are two or more device types, vendors or products are identiﬁed simultaneously on one IP address, it can be detected as a NAT device sharing the IP by multiple devices. Undoubtedly, this feature depends on the high accuracy of TVP ﬁngerprinting identiﬁcation.

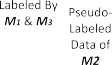
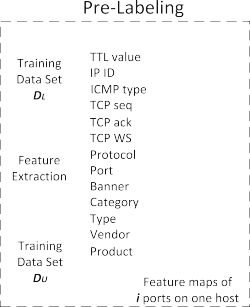
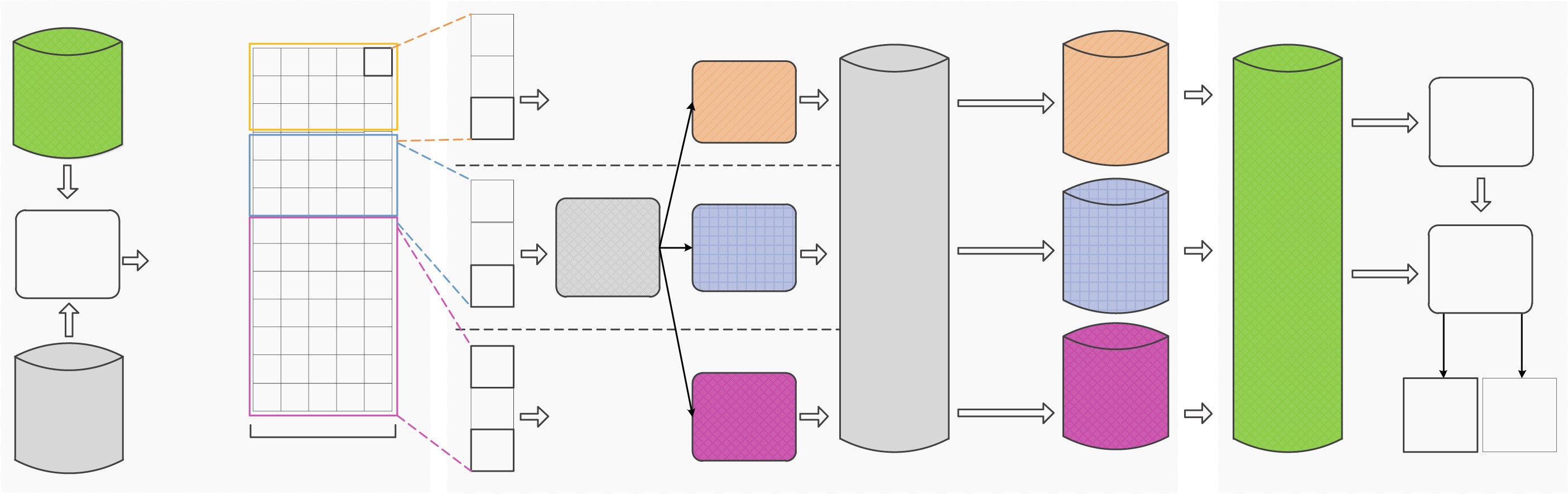
Although features on the application layer behave more obvious than other lay- ers, there is still a key limitation: features on the application layer mainly depend on multiple dimensional ﬁelds on two ports or more. However, these are about two-thirds of online devices in our experimental data set, that have the only open one port on the Internet, features on the application layer can not be eﬀective in the single banner. Hence, we still need to employ other features on the network or transport layer to detect these single-port devices are whether NAT or not.

# Methodology

In this section, we introduce our architecture and the deep learning algorithm for detecting NAT devices base on Tri-net.

## Overview

As illustrated in Fig. [1](#_bookmark4), the workﬂow of our approach has three steps: pre- labeling, label learning, and detection. After labeled a part of instances, the training data set can be extracted features on three layers. Along with the label learning process, training data set can be enlarged and the modules of Tri-net can be trained for NAT detection as the last step. First of all, the features which are depicted in detail as follows.



**Fig. 1.** The main system architecture.

## Pre-labeling

As the ﬁrst step of our approach, we need to conduct a part of the original data set as the training data *DL* = (*Hli, yl*) *l* = 1*,* 2*, ..., L* with *L* labeled instances in advance.

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**Features Extraction.** An active IoT device *Hli* (*l* = 1*,* 2*,... , L*) may open *i* (1 *i*) ports on the Internet, we deﬁne a group of feature values on one port of *Hli* as an instance. Among which, the values of the referring features are divided into *Ni* = [*ttli, idi, icmpi*] on network layer, *Ti* = [*sni, ani, wsi*] on transport layer, and *Bi* = [*bi*1*, bi*2*, bi*3*, ..., bij*] where *bij*(1 *j* 7) on application layer.

*≤*

*≤ ≤*

And *yi* is deﬁned for the detection result where *yi* = 1 if the current host is connecting on the Internet via NAT, otherwise *yl* = 0 means it is directly con- necting on the Internet via the real public IP address or unable to determine. Based on the limit and eﬀective features *Ni*, *Ti* or *Bi* on the three layers that we have discussed in Sect. [3](#_bookmark1), we can respectively label three small data set ,

*DN*

*DT* , and *DB*. Then the data set *DL* = *DN* 丿 *DT* 丿 *DB* can be the input of the

NAT detection training neural network which automatically learns the respec- tive features from each other layers to label the unlabeled instances. We denote the remaining unlabeled data set *DU* = ((*Hui*) *u* = 1*,* 2*, ..., U* with *U* unlabeled online IoT devices.

*|*

## Label Learning

In the second step, the unlabeled instances in *DU* need be automatically labeled as *N AT* or *other* and added into *DL* by synchronized training Tri-net through learning features.

**Modules.** Considering the faults of traditional NAT detecting algorithm and the weak crossing of the features on three independent layers, we employ the Tri-net as our semi-supervised approach [[4](#_bookmark16)]. Since the feature map has been allocated as the input of a shared initial modules *M*0 to generate three diverse modules *M*1, *M*2, and *M*3 for each layer, we can simultaneously train *M*0, *M*1, *M*2, and *M*3 modules. Then, we explore to use Tri-net for learning their particular features and training these modules.

Each module is an independent multi-layer feedforward neural network that can be trained to classify a device with one port. The input layer receives a vector ( *x*1 to *xi*) and the values of *i* feature where *x* belongs to *Ni*, *Ti* or *Bi* on the three layers. And the output layer refers to the classiﬁed result where 1 denotes *N AT* device and 0 denotes *other* ( non-NAT or undetermined). With regard to the number of the hidden layers, we chose diﬀerent optimum nodes in the *i* hidden layers according to more than twice the largest number of neurons in the input layer. Then, the neural network can be initialized for simultaneously training each module.

With the training process in multiple rounds with the increasing labeled data set, three modules *M*1, *M*2, and *M*3 become more and more similar. Considering the logical regression two-category classiﬁer of our neural network, we deﬁne the probability *pj* [0*,* 1] calculating function of the three modules *Mv* (*v* = 1*,* 2*,* 3)

*∈*

as follows:

*pj* =

*ezj*

Y2

*ezk*

*,* (1)

*k*=1

where *ezj* is an exponent of network output for category *j*. And the cross-entropy loss function *Loss* is:

*L* 2

*Loss* = 1 、、*y*

*L*

*j*

* log(*pj*)*,* (2)

1 *i*=1

where *L* denotes the total number of samples in training dataset *DL* and

*yj ∈ {*0*,* 1*}* denotes the labeling result.

**Pseudo-label Editing.** The three modules *Mv* (*v* = 1*,* 2*,* 3) may generate diﬀerent labeling results of one instance *Hli* based on their local features. For solving the divergence, we introduced the *pseudo label* strategy to denote the intermediate results which are produced by the independent modules. If one instance *x* is simultaneously predicted as the same pseudo-labels of the other two modules, that the same result of *x* will be voted as the ﬁnal label. If *x* is diﬀerently predicted as *N AT* and *other* by the other two modules, it will not be labeled for continuous training in the next ground. For one instance *x* in *M*1, if it has been both determined as a *N AT* device by *M*2 and *M*3, that *x* will be as *N AT* by our algorithm. Then the new labeled instance will be added into the training data set for the renewed training of *M*1. With regard to the unseen instance *M*1 which has been denoted as *other* by both *M*2 and *M*3 after three rounds, it will be dropped from the training data set to avoid degenerating the performance.

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For determining the ﬁnal label for *Hi* with its single port with three diverse pseudo-labels *Mv*(*M*0(*Hi*)) and posterior probability *pj*, we employ the Maxi- mum posterior probability (MAP) as follows:

*yj* = *arg* max *p*(*M*1(*M*0(*Hi*)) = *yj Hi*)

*y }{ |*

*j∈{*0*,*1

+ *p*(*M*2(*M*0(*Hi*)) = *yj|Hi*)+ *p*(*M*3(*M*0(*Hi*)) = *yj|Hi*)*}*

## Detection

(3)

After the training process, we got the steady modules *Mv* (*v* = 1*,* 2*,* 3) and the stable labeled training dataset *DL*. With regard to the host *Hl* in *DL* may open *i*(1 *i* 65*,*535) ports on the Internet. That means *i* multiple diverse labels can be produced in the training process. Hence, we employ k-Nearest Neighbors (kNN) to identify the ﬁnal result infers the brand and model of a host *Hl*. In detail, we ﬁrst calculate the distance between *Hli* its labels *yij* on each port every port *Hlj*. The ﬁnal NAT detection result is determined by the closest distance in the trained dataset *DL*.

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# Experiments and Result

In this section, we implemented the experiment to perform the actual validity and accuracy of our approach with real data on the Internet.

## Experimental Data

**Original Data Set.** Considering the adversarial behavior of active port scan on the Internet and ethical guidelines which we must be followed [[5](#_bookmark17)], we employed three open data sets [[6](#_bookmark18), [15](#_bookmark27), [16](#_bookmark28)]. While there are no existing NAT labels in the three original data set. Thus, we need to label parts of the hosts as NAT or not by our pre-labeling algorithm and the above-mentioned feature ﬁelds.

With regard to the banners in three data set, device type, vendor and product can be identiﬁed by using the ﬁngerprinting method [[7](#_bookmark19), [19](#_bookmark31)]. After data processing and device ﬁngerprinting, we take advantage of 7,197,713 public IP addresses with the identiﬁed IoT devices as our experimental data set. Due to multiple devices may share the same IP by NAT or a device may simultaneously open multiple ports on one IP address, we denote one port on one IP as one instance. As illustrated in Table [2](#_bookmark6), 8,644,288 instances have been classiﬁed 4 device cat- egories, including 41 device types, 1,598 vendors, and 11,253 products. Among which, the routing or switching category devices are only identiﬁed based on the general protocol banners. And the other category devices may be identiﬁed based on the general or special protocols. For one instance, a Dell Printer can be identiﬁed as its device type and vendor on both HTTP and PJL Raw services.

**Table 2.** Experimental data set and identiﬁcation result.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Category | Protocol | Port | IoTs | NATs | Type | IoTs | NATs |
| General | FTP | 21 | 300*,* 858 | 156*,* 974 | Router | 1*,* 193*,* 270 | 238*,* 252 |
| SSH | 22 | 310*,* 538 | 35*,* 649 | Gateway | 502*,* 021 | 312*,* 893 |
| Telnet | 23 | 468*,* 732 | 84*,* 522 | UTM | 431*,* 806 | 33*,* 218 |
| HTTP | 80 | 3*,* 295*,* 851 | 916*,* 489 | Switch | 153*,* 539 | 18*,* 647 |
| SNMP | 161 | 520*,* 363 | 175*,* 276 | Modem | 136*,* 479 | 64*,* 864 |
| HTTPs | 443 | 2*,* 780*,* 104 | 860*,* 725 | VPN | 37*,* 332 | 12*,* 509 |
| UPnP | 1900 | 89*,* 453 | 16*,* 978 | Firewall | 16*,* 122 | 11*,* 550 |
| Monitor | RTSP | 554 | 498*,* 917 | 146*,* 956 | NVR | 802*,* 201 | 260*,* 146 |
| ONVIF | 3702 | 308*,* 249 | 70*,* 413 | DVR | 764*,* 100 | 156*,* 875 |
| Printing | LPD | 515 | 63*,* 721 | 11*,* 718 | IPcam | 763*,* 963 | 172*,* 482 |
| IPP | 631 | 17*,* 177 | 4*,* 936 | Printer | 438*,* 421 | 156*,* 449 |
| PJL Raw | 9100 | 26*,* 233 | 10*,* 560 | Scanner | 4*,* 675 | 1*,* 633 |
| Industrial control | Siemens S7 | 102 | 826 | 411 | PLC | 11*,* 742 | 6*,* 754 |
| Modbus | 502 | 19*,* 730 | 10*,* 945 | HMI | 1*,* 799 | 778 |
| PCworx | 1962 | 676 | 293 | RTU | 647 | 432 |
| Ethernet/IP | 44818 | 6*,* 720 | 3*,* 243 | SCADA | 442 | 262 |
| BACnet | 47808 | 9*,* 847 | 5*,* 431 | DCS | 364 | 243 |
| Total | - | *−* | 8*,* 644*,* 288 | 2*,* 511*,* 499 | Other | 3*,* 385*,* 980 | 1*,* 063*,* 512 |

**Pre-labeling.** Based on the features on the network, transport, application layer which has been discussed above, we separately labeled three labels *N*1, *N*2, and *N*3 of the devices. Due to not all features on the three layers that can be covered for some devices, only part of the devices can be labeled, and three labels *N*1, *N*2 and *N*3 may can not be all labeled for these devices. In essence, there also exist conﬂicts among three labels of *N*1, *N*2, and *N*3 on one port or multiple ports of some hosts. This condition does not aﬀect the training process

because these labels are only pseudo-labels for the neural network model to determine the devices are NAT or not ﬁnally. After the pre-labeling process, we got a *DL* labeled data set with 50*k* instances and the remaining unlabeled data set *DU* with more than 8 million instances. In this case, the labeled instances only occupy the low rate of 6*.*2% of the total instances.

**Training Process.** In order to label the unlabeled instances in *DU* to be labeled and added into *DL*, we have programmed our aforementioned Tri-net method of the training neural network in Python. For semi-supervised training the shared initial modules *M*0 to generate three diverse modules *M*1, *M*2, and *M*3 for each layer, we ﬁne-tuned diﬀerent structures and depths for *M*1, *M*2, and *M*3 to adjust their diverse input feature maps. Then, we denote *N*4 for the synthesize labeling result which is determined by the stable pseudo-labels *N*1, *N*2, and *N*3 of three layers.

We implemented the training program on a Lenovo server with two Intel Xeon CPU E5-2650 v4, 256 GB 2400 Mhz memory chips and two NVIDIA Tesla K80 graphics cards. It has taken about 49 h until the training process ended and the stable data set *DL* with 6,318,165 instances were labeled. Eventually, 1,704,833 instances are dropped out because they can not be judged whether NAT or not.

**Table 3.** Experimental result of detecting NATs performance.

|  |  |  |  |
| --- | --- | --- | --- |
| Category | Precision | Recall | F1 score |
| Routing | 0.924 | 0.911 | 0.917 |
| Monitor | 0.943 | 0.937 | 0.939 |
| Printing | 0.953 | 0.968 | 0.960 |
| Industrial control | 0.967 | 0.944 | 0.955 |
| Average | 0.930 | 0.922 | 0.926 |

**Identiﬁcation.** As shown in Table [2](#_bookmark6), 2,511,499 instances are determined as NATs, that account for 29*.*1% percent of total 8,644,288 instances. With regard to the IoT devices which only open one port on the Internet, 5,845,382 instances in our experimental data belong to the single-port class. Among which, 1*,* 692*,* 384 instances are identiﬁed as NATs.

According to our statistics, 1,352,331 IP addresses were shared by more than two ports. Based on the kNN identiﬁcation algorithm, 538,596 IPs are recognized as NATs. Overall, 2,130,980 IPs can be detected as NAT, which nearly rating one-third of the total 7,197,713 IPs of experimental data set.

## Evaluation

**Measurement.** To evaluate the performance of our approach, we introduce two evaluation indexes: precision and recall. Precision reﬂects the rating of NAT devices correctly classiﬁed, which is calculated using Eq. ([4](#_bookmark8)):

*TP*

*Precision* =

*TP* + *FP*

(4)

where True Positive (TP) denotes the number of NAT devices correctly classi- ﬁed as NAT, False Positive denotes the number of non-NAT devices incorrectly classiﬁed as NAT and False Negative (FN) reﬂects the number of NAT devices incorrectly classiﬁed as Other (i.e. non-NAT devices). On the other hand, recall reﬂects the number of Other devices incorrectly classiﬁed as NATs using Eq. ([5](#_bookmark9)):

*TP*

*Recall* =

*TP* + *FN*

(5)

Naturally, high precision and recall are the desirable outcomes. And the har- monic means of precision and recall F1 is calculated using Eq. ([6](#_bookmark10)):

*F* 1 = 2 *∗ Precision ∗ Recall Precision* + *Recall*

(6)

**Veriﬁcation Result.** The detailed performance is revealed in Table [3](#_bookmark7). We observe that the precision of monitor devices is lower than the other categories because of the NAT functional components of themselves. Experimental results show that it is eﬃcient and robust for detecting NATs of online IoT devices based on the features of three layers and the Tri-net method with high precision and recall rate.

100

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|  |  |  |  | |  |  | |
|  |  |  |  | N1-Network Layer N2-Transform Layer N3-Application Layer N4-Final result | | |  |
|  |  |  |  |  |
|  |  |  |  |

95

90

85

Recall(%)

80

75

70

65



60

88 90 92 94 96 98 100

Precision(%)

**Fig. 2.** The precision and recall of features on three layers.

**Feature Eﬀectiveness on Three Layers.** As shown in Fig. [2](#_bookmark11), X-axis and Y-axis separately indicate the precision and recall of the diverse features on net- work, transport and application layers. That obviously indicates that features

on the application layer have the highest precision and recall, and the trans- port layer has the lowest performance. The diﬀerence depends on the feature eﬀectiveness of three layers. For example, the variation of TCP sequence and acknowledgment number between NAT and non-NAT is not obvious.

# Conclusion

In this paper, we presented a new approach based on Tri-net for active NAT detecting with eight features on three layers. Through experimenting on real Internet open data, we found almost one-third of online IoT devices using NATs to connect to the IPv4 space. Among the four IoT categories, industrial control devices are more using NAT than routing, printing, and monitor. The ﬁnal eval- uation of our measurement revealed the precision and recall both can be up to 92%. With the wide deployment of IPv6, a further test would be to identify NAT on intelligent devices which are connected to Internet via IPv6.

**Acknowledgments.** This work was supported by National Key R&D Program of China (Grant 2017YFC0820701), National Natural Science Foundation of China (Grant U1766215, 61702504).

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