Classifying Network Vendors at Internet Scale

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ABSTRACT
In this paper, we develop a method to create a large, labeled dataset of visible network device vendors across the Internet by mapping network-visible IP addresses to device vendors. We use Internet-wide scanning, banner grabs of network-visible devices across the IPv4 address space, and clustering techniques to assign labels to more than 160,000 devices. We subsequently probe these devices and use features extracted from the responses to train a classifier that can accurately classify device vendors. Finally, we demonstrate how this method can be used to understand broader trends across the Internet by predicting device vendors in traceroutes from CAIDA’s Archipelago measurement system and subsequently examining vendor distributions across these traceroutes.

1 INTRODUCTION
Understanding the prevalence of different network device vendors can lend insights into the robustness (or fragility) of the underlying infrastructure. These devices run software that can contain vulnerabilities [24, 23, 12, 6, 26, 5], and concerns have been raised about the possibilities of “backdoors” [16]. Users and organizations may want better ways to gain insights into the vendors of devices that are deployed in different parts of the network; nations may also be interested in gathering this intelligence on a broader scale.

Despite the benefits of fingerprinting network devices, doing so at scale, remotely, is challenging. One challenge is gathering enough data to develop models that can accurately classify devices by manufacturer. Scanning devices across the Internet is costly enough, but even given data from Internet scans, the data lacks labels.

In this paper, we develop a method that can associate network devices with vendors. The first step of the process involves compiling a large, labeled dataset of more than 160,000 IP-visible network devices across the Internet; for this part of the process, we use banner grabs from SSH, Telnet, and SNMP to associate labels with corresponding network-level devices. More specifically, we use a novel clustering approach to extract vendor labels from banners. Second, we develop a probing technique that elicits responses from these devices and can be used at scale, build a feature set based on these responses, and train a classifier that predicts a vendor that corresponds to an IP address with over 90% accuracy. This second step is critical in allowing us to conduct a large-scale survey of network devices: rather than only being able to classify devices that have open SSH, Telnet, or SNMP ports, we can now classify any device that responds to the measurement probes that we send.

The resulting measurements contain some sampling bias—in particular, the resulting set only represents measurements of devices that are visible at the network layer and that respond to the probes. Yet, assuming that any resulting conclusions account for this bias, the set of measurements is considerably larger than any existing dataset of its kind and allows researchers to garner new insights from existing datasets.

Such a labeled dataset has considerable utility for the measurement community, including the ability to augment existing datasets with these labels. We demonstrate the insights that a model trained on a labeled dataset can yield by assigning labels to network IP addresses in the CAIDA Archipelago traceroute dataset and exploring the differences in the distribution of vendors on traceroutes from the United States and Germany destined to different continents.

2 GENERATING LABELED DATA AT SCALE
Figure 1 shows our pipeline for classifying network devices at scale. The first step in the pipeline involves creating a dataset that associates IP addresses with labels of different device vendors. As with many supervised machine learning problems, acquiring or generating a large labeled dataset can be a significant challenge. In this section, we present the method we develop for generating and curating such a dataset and describe the properties of the resulting dataset.

More specifically, we combine clustering techniques with Telnet, Secure Shell Protocol (SSH) and Simple Network Management Protocol (SNMP) banners to aid in identifying the vendor of a given device. Connecting to devices through
these protocols can elicit a banner, which can then be examined to determine the vendor of the device. While we use the methods in this section to label network devices, the approach can be generalized to other problem domains.

### 2.1 Banner Grabs

**Candidate IP Addresses.** As our goal is to classify network devices, not end hosts, we rely on the CAIDA Macroscopic Internet Topology Data Kit (ITDK), which provides us with an IPv4 router topology [3]. The topology is produced from traceroutes from December 24, 2019 to January 7, 2020 from 159 vantage points in 50 different countries. The topology provides us with over 100 million IP addresses associated with routers across the Internet, the ability to map each IP address to its corresponding router, and a mapping from each network device to the ASN controlling it.

We grab the banners for each of the over 100 million IP addresses in the IPv4 topology using zgrab2 [14]. Zgrab2 supports SSH and Telnet banner grabs by default, and we build a custom module for SNMP banner grabs. Table 1 examines the magnitude and rate of response of this process at different granularities. We see that although a small percentage of devices respond to the requests, almost 2 million unique devices respond to one of the banner grabs. Furthermore, these devices are spread across over 18,000 ASes, accounting for over 30% of the ASes we probed.

### 2.2 Labeling

Given the set of IP addresses and corresponding banners, we attempt to match each IP address with a vendor.

#### 2.2.1 Vendor name matching

We first try a simple, intuitive heuristic of matching an IP to a vendor label by searching for vendor names directly inside the banners. We collected a list of 40 network vendors from Wikipedia [17]. We present the full list in Appendix A.1. Table 2 shows the results of this method. We immediately see that Cisco dominates the results. Upon inspection, we find that Cisco has a branded SSH version which contributes to many of the labels.

This approach extracts an adequate amount of labels for some vendors, but can miss many phrases in the banners that may indicate the vendor of the router without actually including the vendor’s name. Furthermore, vendors with more generic names will cause many conflicts or inaccurate labels using this method. For example, searching for “extreme” for Extreme Networks may include generic text about “extreme consequences for unauthorized connections.” We encountered 168 conflicts using this approach where one banner matched multiple different vendor names.

#### 2.2.2 Clustering

We now develop a more sophisticated approach to labeling IP addresses, based on the intuition that vendors configure devices with default banner formatting that is often unique to a particular vendor. This default formatting may contain vendor names, model numbers, warning messages, login prompts or other technical phrases or sequences of characters that can be matched to a vendor through web searches. By collecting these phrases, we are able to label significantly more devices for many vendors and also discover new vendors.

We design an iterative clustering algorithm to search for potential matching phrases or “fingerprints.” Clustering banners is a unique challenge that is not easily compatible with standard bag-of-words NLP models. Banner texts are overall very similar, and features such as word ordering of arbitrary lengths and whitespace can be very indicative. In addition, terms that differ by one character (such as model numbers) may still be strongly related, and the clustering should group them together. We therefore cluster banners using their pairwise edit distances, which preserves banner structure.

We iteratively cluster random samples of unlabeled IP addresses, and use these clusters to generate fingerprints. Take $N$ to be the dataset of banners. For each banner protocol, we repeatedly sample $M$ IP addresses from $N$ where $M \leq 1000$ (explained at the end of this section). For each sample, we compute an $M \times M$ symmetric edit distance matrix, where $M_{i,j} = M_{j,i}$ is the edit distance between banner $i$ and banner $j$. Specifically, if $\text{len}(i) \leq \text{len}(j)$, we compute $M_{i,j}$ by finding the Levenshtein edit distances between $i$ and all $\text{len}(i)$-length substrings of $j$ and taking the minimum distance.

We then perform clustering on matrix $M$ for each banner protocol using HDBSCAN* [19]. We set $\text{min\_cluster\_size}$ and $\text{min\_samples}$ to 5, which causes HDBSCAN* to aggressively form small, tight clusters. HDBSCAN* also produces “noise” clusters for banners that do not strongly cluster, which we discard.

For each non-noise cluster, we identify potential fingerprints by computing the matching sequences of characters between all combinations of banners and sorting them by frequency. We then link the most frequent sequences to vendors by manually searching on Google, Shodan, and Censys [7]. Possible links include vendor names, model numbers, router documentation books, vendor support forums and mailing lists, blog posts, and other banner protocols (e.g. FTP). For example, routeros ccr1 is from a MikroTik router family, and welcome to zxr is from a ZTE router family.

If we encounter multiple similar fingerprints in a cluster, we manually create a regex fingerprint to capture them. For

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1 CAIDA’s ITDK contains two topologies, one optimized for accuracy of aliases and one optimized for coverage of aliases. We use the topology optimized for accuracy.

2 SNMP “banners” are collected with a bulk query for \*System\* records.

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example:

```bash
\(ttyp[\d\w]\)\r
\r
login
```
is used very frequently by Juniper routers. If a fingerprint can be linked to multiple vendors or a misleading resource, such as a textbook or enterprise customer, we ignore it. We also create a “blacklist” for fingerprints linked to consumer routers or endpoints, which we exclude from labeling.

After clusters of matrix $M$ have been examined, we apply our current set of fingerprints to all IP addresses and resolve conflicts that arise. Since we label the entire set of IPs after each iteration of clustering, each iteration may significantly reduce the remaining sample space of unlabeled IP addresses, so choosing sampling small matrices $M$ is sufficient.

### 2.2.3 Conflict resolution.

Conflicting labels can arise when 1) a short fingerprint matches too many banners as part of a longer sequence, or 2) devices include sequences from other vendors in their banners. If we can confidently identify the most likely vendor of a set of conflicts after additional web searches or close inspection, we set that vendor’s fingerprint to supersede the other. For example, we found SNMP banners which contained fingerprints for H3C or MikroTik as well as Huawei. On closer inspection, we determined them to be H3C or MikroTik routers owned by Huawei, as they also included H3C or MikroTik model numbers and OS versions.

If a fingerprint creates conflicts with more than one vendor, we remove the fingerprint. For example:

```bash
user access verification\r\n\r\n\nusername
```
is a well-established Cisco Telnet banner fingerprint, and it appears in Recog, an open source fingerprint database [22]. Clustering identified this fingerprint, and this fingerprint matched over 20,000 Cisco devices as well as devices with fingerprints from four other vendors.

### 2.2.4 Results.

Ultimately, we are able to identify 30 different vendors and label over 175,000 IP addresses using our clustering approach, while our blacklist filters out an additional 140,000 consumer or endpoint devices. Clustering produced fewer than 20 conflicts throughout the entire process, compared to 168 conflicts from the vendor name matching approach, which provides confidence that the process generates fingerprints with sufficiently low entropy. Table 2 shows the most frequently labeled vendors.

We find many banners without vendor-specific phrases which cannot be assigned a label. For example, 93% of SSH banners only contain versions of Linux or general SSH servers such as OpenSSH and Dropbear. Common reasons we were not able to associate banners with vendors were short authentication prompts (login: or password), client-side SSH errors (connection closed by remote host) or empty banners. Lastly, banner structures which appear very infrequently in our dataset are likely filtered out by HDBSCAN* into the “noise” cluster.

Note that this approach is susceptible to introducing errors or failing to detect conflicts, due to incomplete research, banner data, or fingerprints, as well as devices which impersonate other vendor banners. For our purposes, a small amount of noise in labels will have a negligible impact on classifier performance. More broadly, despite these potential pitfalls, our method provides the first fingerprint dataset targeting network vendors learned from clustering and backed by web research, and we show this is a promising approach for future label generation.

### 3 CLASSIFYING NETWORK DEVICES

To classify network devices at scale, we need to compile a set of probes that elicit unique responses from each network device vendor, extract a set of features from the responses, and

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Note that we treat all output from zgrab as banners. While that can include certain client-side prompts and errors, our approach to clustering filters those types of banners from our classification.
and train a model to distinguish the vendors using those features. There are many challenges to fingerprinting network devices at scale which must be acknowledged. A subset of devices are not visible at the IP layer, and some devices may not respond to probe-based measurements. We cannot fingerprint these devices with our techniques. Furthermore, a single IP-visible device can be associated with multiple IP addresses. We mitigate double counting labeled devices by de-aliasing IP addresses to a single device. Finally, we must use our smaller set of labeled devices, which may not fully represent the larger set of unlabeled devices, to train a model for classifying unlabeled devices. We acknowledge there may be bias in our labeled dataset but still believe it to be the most principled approach to tackle the challenge of classifying network devices at scale.

3.1 Network Device Probes and Features

Many devices, such as web servers, have a standard port that is open for connections. Many network devices, on the other hand, have no such port. One option is to find an open port by scanning the ports of each device before probing. Unfortunately, this is not scalable and, even worse, many network devices may have no open ports at all. As such, we only consider probes that either require no port or that are specifically sent to closed ports on the target machine.

3.1.1 Nmap. Probes. Nmap is perhaps the most popular active OS fingerprinting tool and has been developed for over 20 years [18]. Nmap’s OS fingerprinting system is thorough, first scanning the 1,000 most popular open ports on a device to find an open port. It then sends up to 16 specially crafted TCP, UDP, and ICMP probes to the device that are intended to invoke a unique response. While 10 of these probes are sent to an open port, 6 of these probes (3 TCP, 1 UDP, 2 ICMP) are sent specifically to a closed port on the device. The 3 TCP probes differ in their options and flags, the UDP probe is sent to elicit an ICMP error message from the remote device, and the 2 ICMP packets are ICMP echo packets with differing types and IP header values. More details on these probes can be found in Appendix A.2. We use these 6 probes as a base set of probes to send to each IP address.

**Probe implementation.** We directly port the Nmap closed port probes above into Zmap to facilitate fingerprinting large amounts of devices quickly [8].

**Feature extraction.** Nmap transforms the responses it receives into features by applying a series of tests on each packet. These tests have been developed for over 20 years. Table 7 in Appendix A.4 shows the list of features that correspond to the closed port probes that we use for the scans. These features include the options and order of options in the TCP headers, the behavior of the sequence and acknowledgment numbers in the TCP responses, and the IP initial time-to-live of the responses.

3.1.2 ICMP. Probes. ICMP provides a unique avenue for useful probes as the protocol is not directed to a particular port, meaning we can send an ICMP message to a network device with no open ports and still receive a response. Furthermore, some network device OSes may restrict access to valid ICMP requests that can be used for fingerprinting, such as ICMP timestamp requests, giving insight into the vendor of the device just by the response (or lack thereof) to the probe [15]. While Nmap incorporates ICMP probes in its fingerprinting system, it only sends two ICMP echo probes, omitting a wide variety of ICMP messages that can be sent.

We expand on the set of probes that we can use for fingerprinting through ICMP fuzzing. More specifically, the ICMP protocol contains a type field that currently has 34 standardized types. Many of these types contain a code field that specifies sub-types of each message, such as an explanation for the error that was returned. We enumerate these standardized types and codes by sending a valid ICMP message for each pair to each device in the labeled dataset.

**Probe implementation.** We develop an ICMP fuzzing system using Scapy that sends a valid ICMP message for each implemented ICMP type and code to each remote device [2].

**Feature extraction.** We extract each header field and value of the ICMP responses and encode them as a categorical feature for the fingerprints. A subset of these features are shown in Table 7 in Appendix A.4. Features include the type and code of the ICMP response, the data in the address mask reply, as well as the ICMP ID and sequence number fields.

3.2 Network Device Classification

We use the dataset of labeled network devices (Table 2), and our set of probes and features to train a model that predicts the class of a fingerprint. In this section, we outline our

| Manufacturer | IP Address Labels: Regex Match | Clustering | Network Device Labels: Responsive |
|--------------|--------------------------------|------------|-----------------------------------|
| Cisco        | 63,990                         | 85,379     | 83,592                            |
| Mikrotik     | 9,700                          | 39,243     | 38,134                            |
| Huawei       | 17,134                         | 17,075     | 16,210                            |
| H3C          | 10,231                         | 10,620     | 10,183                            |
| NEC          | 8                              | 6,934      | 6,918                             |
| Lancom       | 4,372                          | 4,282      | 4,098                             |
| Juniper      | 59                             | 4,255      | 4,065                             |
| Adtran       | 1,741                          | 3,527      | 3,497                             |
| ZTE          | 2,462                          | 2,318      | 2,226                             |
| Ubiquoss     | 8                              | 1,887      | 1,869                             |
| Dell         | 59                             | 1,883      | 1,849                             |
choice of model, methods use to train the model, and metrics for evaluating the trained model.

3.2.1 Model. We consider each feature extracted in Table 7 as a categorical feature. We use a one-hot-encoding (OHE) to transform each categorical feature into \( n \) binary features, where \( n \) is the number of unique values found in the original categorical feature. We use a random forest model for classification, motivated by the expectation that specific feature interactions will be important for performance. Furthermore, choosing a random forest model allows us to easily interpret which features are driving the performance of the trained model.

3.2.2 Metrics. We evaluate the trained models using accuracy, ROC AUC, and F1 scores. More specifically, we use a balanced accuracy score to account for any class imbalance in the data, in which each sample is weighted according to the inverse prevalence of its true class. This dataset represents a multiclass classification problem. We consider ROC scores in a “one-vs-rest” fashion, where each class \( C \) is considered as a binary classification task between \( C \) and all other classes. Furthermore, we use a “micro” averaged F1 score, which counts the total number of true positives, false positive, and false negatives. We present the average metrics for a five-fold cross validation.

3.2.3 Pipeline Evaluation. We probe each IP address in the labeled dataset, retrying each probe up to three times. For each probe requiring a port, we choose a high numbered port at random for each scan (every IP is scanned on the same ports). Choosing a high-numbered port increases the likelihood of the port being closed. At this point, we remove any IP address from the labeled dataset that did not respond to any probes. After removing unresponsive IP addresses, we dealias the network devices using the topology provided by CAIDA’s ITDK. We then filter the number of vendors down to the final set shown in Table 2 by examining a large reduction in vendor labels (\( \sim 500 \) devices) from the 11th most labeled vendor vendor to the 12th. We do not consider devices outside of these 11 classes for our evaluation.

To address the class imbalance (Table 2), we balance the classes before training the model to avoid trivializing the task for the model (learning to predict everything as Cisco). Specifically, we downsample the Cisco and Mikrotik classes to 17,000 samples, which is in line with the 3rd most prevalent class in the dataset.

We use scikit-learn’s implementation of a random forest classifier to train and test models [20]. One-hot encoding each feature in Table 7 results in more than 1,000 features. Scikit-learn’s random forest implementation computes the importance of each feature in the model using the Gini feature importance, which we use to better understand the model. We perform a randomized hyperparameter search of 50 different models, varying the number and depth of trees, the maximum number of features used by the trees, the minimum samples required for internal and leaf nodes, if bootstrapping is used, and the function used to measure split quality. We perform three-fold cross validation on each model where each fold preserves the percentage of the samples in each class across the entire dataset. We choose the best performing model with respect to test accuracy to evaluate using five-fold cross validation.

Table 3 shows the mean accuracy, ROC AUC, and F1 scores resulting from five-fold cross validation using different sets of features. Here, we note that the dataset contains 11 classes, so a random guess of the class by the model would result in approximately 9% balanced accuracy score. Table 3 shows that Nmap’s closed port probes perform well on their own, reaching an F1 score of over 85%. Furthermore, we see ICMP fuzzing was relatively successful, but not as accurate as the more nuanced Nmap probes. We inspect the features of the ICMP model to determine which probes are driving its performance. Ultimately, three probes contribute to almost all of the model’s performance: the ICMP echo probe, the ICMP timestamp probe, and the ICMP address mask probe. We train the final model using Nmap’s closed port features, the ICMP address mask probe, and the ICMP timestamp probe (Nmap’s probes already contain two ICMP echo probes). We see that adding these two probes improves the accuracy of the classifier by over 13%, and the F1 score of the classifier by 6% to 93%. Overall, by only sending 8 network packets to a closed port, with our methodology, we can identify a device vendor with 91.9% balanced accuracy. Figure 2 in Appendix A.4 shows ROC and PR curves of the final model.

Finally, we examine the model to determine which features are important. Table 7 shows the feature ranking of each feature in the classifier. We see that the most important feature for the classifier is the initial TTL of the packet sent in response to the probes. We also see that many of the features added from ICMP fuzzing lie in the top 10 features of the classifier.

| Features                        | Balanced Accuracy | ROC AUC | F1  |
|---------------------------------|-------------------|--------|-----|
| Nmap                            | 77.3              | 0.97   | 86.1|
| ICMP                            | 54.3              | 0.91   | 73.7|
| Nmap + Top ICMP                 | 91.9              | 0.99   | 93.7|
4 INSIGHTS ABOUT INTERNET PATHS

To demonstrate the types of new insights that device classification can yield for existing Internet measurement datasets, we collect a candidate set of network devices that are likely active by parsing traceroutes from CAIDA’s Archipelago (Ark) infrastructure [4], exploring a snapshot of the Internet topology by downloading and parsing Ark traceroutes from May 27, 2020, which yields network device IP addresses. We collect a fingerprint for each IP address using Zmap, then use the classifier trained in Section 3 to predict a class (i.e., vendor) for each IP address. We determine the threshold for the classifier that provides the best F1 score; if the classifier cannot predict a class with at least that level of confidence, we assign an “unknown” label to the IP address.

Table 4 shows that many more IP addresses the CAIDA Ark dataset are unresponsive to probes than in the labeled dataset. Table 6 in Appendix A.3 shows the difference in response rates for each specific probe in the labeled dataset and the CAIDA measurement.

We categorize traceroutes based on the location of the source (i.e., country of CAIDA Ark node) and destination (i.e., continent of target IP address, based on IP geolocation from geolite2) [10]. We do not use IP geolocation on intermediate traceroute hops due to known inaccuracy of geolocation on infrastructure IP addresses [11]. For each traceroute, we tally the unique vendors that are present and calculate the probability of encountering each vendor over the dataset as: \( \frac{\text{Traceroutes with vendor}}{\text{Total traceroutes}} \). Table 5 shows the results for popular router vendors seen in traceroutes from Arks located in the United States and Germany.

The source countries, United States and Germany, do show some differences in vendor prevalence. Traceroutes from sources in Germany are more likely to include Huawei routers compared to traceroutes from sources in the United States. Interestingly, prevalence of traceroutes from Germany to Europe that Huawei is found on (48.52%) is higher than that of traceroutes from the United States to Europe (36.99%). We also find that traceroutes from Germany have a higher prevalence of ZTE devices, across all target continents. On the other hand, Juniper is less prevalent on the traceroutes originating in Germany.

### Table 4: Distribution of the number of responses from each device in both our labeled dataset and the Internet-wide measurement.

| Dataset   | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|-----------|---|---|---|---|---|---|---|---|---|
| Labeled   | 0.8 | 5.7 | 4.2 | 7.7 | 3.6 | 7.3 | 23.6 | 46.7 | 0.6 |
| Measurement | 23.9 | 2.5 | 9.9 | 15.1 | 5.3 | 4.8 | 13.1 | 22.0 | 3.4 |

### Table 5: Vendor prevalence in CAIDA Ark traceroute dataset, by source country and destination continent.

| Source | Destination | Cisco | Huawei | Juniper | ZTE |
|--------|-------------|-------|--------|---------|-----|
| US     | Africa      | 80.9% | 44.8%  | 81.3%   | 12.3%|
|        | Asia        | 84.5% | 56.0%  | 76.6%   | 29.4%|
|        | Europe      | 72.2% | 37.0%  | 80.7%   | 25.5%|
|        | North America | 65.6% | 27.1%  | 73.1%   | 19.0%|
|        | Oceania     | 86.8% | 35.4%  | 83.4%   | 19.4%|
|        | South America | 83.7% | 43.2%  | 86.1%   | 25.8%|
|        | ALL         | 74.5% | 39.4%  | 77.1%   | 23.7%|
| DE     | Africa      | 86.5% | 58.0%  | 83.6%   | 37.2%|
|        | Asia        | 89.0% | 69.9%  | 75.9%   | 61.5%|
|        | Europe      | 78.4% | 48.5%  | 72.1%   | 46.1%|
|        | North America | 88.1% | 48.5%  | 68.6%   | 63.4%|
|        | Oceania     | 91.1% | 56.5%  | 81.0%   | 45.1%|
|        | South America | 91.3% | 55.8%  | 85.8%   | 45.8%|
|        | ALL         | 86.3% | 55.7%  | 73.1%   | 56.7%|

5 RELATED WORK

Vanubel et al. examined the feasibility of fingerprinting network equipment in 2013 [25]. Specifically, they examine default time to live (TTL) headers in IP packets received by through active probing. They create a signature for each router from the different initial TTLs received from two separate ICMP requests. Our work considers TTL values as a feature for the classification model, but vastly differs in the methods for generating labels, classification, and types of probes sent to each device. Further differentiating our work, we are the first to apply machine learning techniques towards the discovery of network device vendors at scale.

Feng et al. examine the automatic labeling of devices with a rule-based approach [9]. At the vendor label, they look to label devices through the matching of 1,552 vendor names, specifically in the IoT space. Our work differs in that we use clustering to discover more nuanced phrases that map to specific vendors, which we find produces a higher amount of labels with more confidence than regex matching.

Perhaps the most well known tool in active remote device fingerprinting is Nmap [18]. Nmap is a network scanning tool that has developed into the most popular OS fingerprinting tool by using knowledge of the idiosyncrasies in the TCP/IP and the ICMP implementations in different types of devices. Our work makes direct use of Nmap to actively probe devices.

Fingerprinting remote devices purely via ICMP messages was examined briefly by Arkin [1]. Arkin developed X and XProbe to fingerprint remote operating systems solely through ICMP messages by examining the respective responses, like ICMP error message size and integrity. Many of the techniques introduced by Arkin are now part of Nmap.
Kohno et al. introduced the area of remote physical device fingerprinting [15]. The work examined the feasibility of fingerprinting remote devices by examining device clock skews. In this work, we do not consider hardware fingerprinting methods, though we see it as a potential avenue for future work in more granular device fingerprinting.

Raman et al. and Jones et al. leverage clustering techniques to develop fingerprints [21, 13] for ground truth labels. While our work uses clustering techniques to develop fingerprints in the labeling process, we train models using the generated models on a different set of features which allows us to fingerprint previously unlabeled devices at scale.

6 CONCLUSION
Understanding the manufacturers of network infrastructure on a given network is valuable knowledge to multiple parties.

In this paper, we explored the feasibility of classifying network devices at scale. We have generated a labeled dataset of over 160,000 devices using banner grabs, compiled a set of probes that elicit unique responses from devices, trained a classifier to distinguish between multiple vendors, and predicted network device vendors at scale using this classifier. We specifically examine predicting IPv4 network devices in this work, but believe the methodology could be generalized to IPv6 network devices or other device types, such as IoT devices.

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A APPENDIX

A.1 Regular Expression Match

Below are the list of manufacturers and simple regexes used to first match banners to a manufacturer.

| Manufacturer | Regexes       |
|--------------|---------------|
| adtran       | adtran        |
| aerohive     | aerohive      |
| alaxala      | alaxala       |
| allied       | allied        |
| alcatel      | alcatel       |
| aruba        | aruba         |
| asus         | asus          |
| avaya        | avaya         |
| avm          | avm           |
| brocade      | brocade       |
| calix        | calix         |
| cisco        | cisco, "c i s c o" |
| dell         | dell          |
| draytek      | draytek       |
| d-link       | d-link        |
| enterasys    | enterasys     |
| ericsson     | ericsson      |
| extreme      | extreme       |
| fortinet     | fortinet      |
| h3c          | h3c           |
| hpe          | hpe, hewlett  |
| huawei       | huawei        |
| juniper      | juniper, junos|
| lancom       | lancom        |
| linksys      | linksys       |
| meraki       | meraki        |
| mikrotik     | mikrotik      |
| netgear      | netgear       |
| nokia        | nokia         |
| openmesh     | open mesh     |
| ruckus       | ruckus        |
| sierra       | sierra        |
| technicolor  | technicolor   |
| tp-link      | tp-link, tplink|
| trendnet     | trendnet      |
| ubiquiti     | ubiquiti      |
| xirrus       | xirrus        |
| yamaha       | yamaha        |
| zyxel        | zyxel         |
| zte          | zte, zhongxing|

A.2 Nmap Probes

Here we further outline the 6 Nmap probes we used for fingerprinting routers. First, we use 2 ICMP echo (ping) probes. The first ICMP echo probe sets the don’t fragment bit in the IP header to one, sets the IP type-of-service byte to 0, sets the ICMP code to 9 instead of 0, the ICMP sequence number to 295, and sends 120 bytes of 0x00 for the payload. While Nmap randomly sets the IP ID and ICMP request identifier, we use static values in our probes. The second ICMP echo probe sets the IP type-of-service byte to 4, and the ICMP code to 0. It sends 150 bytes of 0x00 instead of 120. Finally, it increases the ICMP request ID and sequence number by one from the first ICMP echo probe.

Nmap sends one UDP probe a closed port on the target machine. This UDP port contains a payload of the character 'C' repeated 300 times. The IP ID value is set to 0x1042. Nmap sends this probe specifically to invoke an ICMP port unreachable message from the target machine.

Finally, Nmap sends 3 TCP probes to a closed port on the target machine. The TCP options for each probe are static, corresponding to a window scale of 10, operation (NOP), a maximum segment size of 265, a timestamp value of 0xFFFFFFFF, and Selective ACKnowledgement (SACK) permitted. The first TCP probe is a TCP SYN packet with a window field of 3137. The second TCP packet is a TCP ACK packet with the don’t fragment bit in the IP header set, and a window field of 32768. The third TCP packet has the FIN, PSH, and URG flags set and a window field of 65,535. Finally, the window scale option on this probe is set to 15, rather than 10.

A.3 Measurement Response Rate

Table 6: Response rates to each probe in both the labeled dataset and Internet-wide measurement.

| Probe          | Dataset | UDP | ICMP Echo 1 | ICMP Echo 2 | ICMP Timestamp | ICMP Address Mask | TCP 1 | TCP 2 | TCP 3 |
|----------------|---------|-----|-------------|-------------|----------------|-------------------|-------|-------|-------|
| Labeled        | 61.6    | 68.3| 96.7        | 70.7        | 13.2           | 80.9              | 77.8  | 72.5  |
| Measurement    | 41.0    | 68.7| 72.3        | 48.8        | 8.2            | 44.5              | 46.1  | 43.0  |

A.4 Classification Features and Performance

See table and figures on the following page.
Table 7: Features extracted from the responses to the sent probes, ranked by their importance to classification.

| Feature                              | Description                                                                 | Source | Rank |
|--------------------------------------|-----------------------------------------------------------------------------|--------|------|
| IP initial time-to-live              | Calculated original time-to-live of in response                             | Nmap   | 1    |
| IP initial-time-to-live-guess        | If unable to calculate initial IP ttl, guess closest of [32, 64, 128, 256]   | Nmap   | 2    |
| Responsiveness                       | Was the probe responded to?                                                | Nmap   | 3    |
| Integrity of returned probe UDP checksum | Is the UDP header checksum value returned as it was sent?                 | Nmap   | 4    |
| TCP RST data checksum                | Is there error data in the TCP reset packet?                               | Nmap   | 5    |
| TCP flags                            | Recorded TCP flags in response                                             | Nmap   | 6    |
| ICMP sequence number                 | ICMP sequence number received in response to ICMP packet                    | ICMP   | 7    |
| ICMP address mask                    | ICMP address mask received in response to ICMP address mask request         | ICMP   | 8    |
| ICMP identifier                      | ICMP identifier received in response to ICMP packet                         | ICMP   | 9    |
| Returned probe ID value              | Is the IP ID value in the response to the UDP probe the same as was sent?  | Nmap   | 10   |
| ICMP code                            | ICMP code received in response to ICMP packet                               | ICMP   | 11   |
| TCP window size                      | 16-bit window size in TCP header of response                               | Nmap   | 12   |
| TCP acknowledgement number           | Comparison of acknowledgement number in response to sequence number in probe | Nmap   | 13   |
| ICMP echo response code              | ICMP message codes received in response to Nmap ICMP echo packet           | Nmap   | 14   |
| TCP options                          | TCP options in response - order preserved                                   | Nmap   | 15   |
| IP don’t fragment bit                | Was the don’t fragment bit set in the IP header?                           | Nmap   | 16   |
| TCP sequence number                  | Comparison of sequence number in response to acknowledgement number in probe| Nmap   | 17   |
| IP total length                      | IP total length of response to UDP probe                                   | Nmap   | 18   |
| Unused port unreachable field nonzero | Are the last four bytes in the ICMP port unreachable message set?         | Nmap   | 19   |
| Integrity of returned UDP data       | Is the UDP data returned exactly as it was sent?                           | Nmap   | 20   |
| ICMP type                            | ICMP message type received in response to ICMP packet                       | ICMP   | 21   |
| TCP quirks                           | Is the urgent pointer field non-zero when URG flag not set?               | Nmap   | 22   |

Figure 2: Visualizing classification performance for different vendors.