How to Achieve High Classification Accuracy with Just a Few Labels: A Semi-supervised Approach Using Sampled Packets

Shahbaz Rezaei
University of California
Davis, CA
srezaei@ucdavis.edu

Xin Liu
University of California
Davis, CA
xinliu@ucdavis.edu

ABSTRACT
Network traffic classification, which has numerous applications from security to billing and network provisioning, has become a cornerstone of today’s computer networks. Previous studies have developed traffic classification techniques using classical machine learning algorithms and deep learning methods when large quantities of labeled data are available. However, capturing large labeled datasets is a cumbersome and time-consuming process. In this paper, we propose a semi-supervised approach that obviates the need for large labeled datasets. We first pre-train a model on a large unlabeled dataset where the input is the time series features of a few sampled packets. Then the learned weights are transferred to a new model that is re-trained on a small labeled dataset. We show that our semi-supervised approach achieves almost the same accuracy as a fully-supervised method with a large labeled dataset, though we use only 20 samples per class. In tests based on a dataset generated from the more challenging QUIC protocol, our approach yields 98% accuracy. To show its efficacy, we also test our approach on two public datasets. Moreover, we study three different sampling techniques and demonstrate that sampling packets from an arbitrary portion of a flow is sufficient for classification.

CCS CONCEPTS
• Networks → Network monitoring; • Computing methodologies → Machine learning; • Information systems → Decision support systems;

KEYWORDS
Transfer Learning, Semi-supervised Learning, Network Traffic Classification, Packet Sampling, QUIC Protocol Classification

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1 INTRODUCTION
Network traffic classification is one of the key components of network management and administration systems. Classical machine learning approaches have been extensively used for more than a decade and showed good accuracy. However, the emergence of new applications and encryption protocols has dramatically increased the complexity of the traffic classification problem. Recently, deep learning algorithms have been developed for traffic classification. Deep learning approaches are capable of automatic feature selection and capturing highly complex patterns, and thus demonstrated high classification accuracy in comparison to other methods.

However, deep learning requires a large amount of labeled data during training. Capturing and labeling a large dataset is a non-trivial and cumbersome process. First, current Internet traffic is mostly encrypted that makes DPI (Deep Packet Inspection) based labeling impossible. Hence, most labeling procedures capture each traffic class in isolation. Furthermore, such a process is often performed through scripts that mimic human behavior. Such scripts are not always accurate, and thus affect classification accuracy (as discussed in detail in Sec. 5.3). In contrast to the difficulties in obtaining labeled data, we note that unlabeled data is abundant and readily available in the Internet. Therefore, it motivates us to study how to use easily-obtainable unlabeled datasets to dramatically reduce the size of labeled dataset needed for accurate traffic classification.
Furthermore, to make our approach practical, in particular in high speed links or data centers, we propose to use sampled time series features instead of an entire flow to do packet classification. This approach also allows us to avoid the dependency on handshake data usually needed for header/payload based approaches. Newer protocols, such as QUIC and TLS 1.3, use 0-RTT feature that reduces unencrypted information exchanged during handshake phase and thus renders header/payload based approaches ineffective. Using sampled packets also reduces memory and computation complexity needed for entire time series features.

In summary, in this paper, we make the following contributions:

1. We propose a semi-supervised approach that utilizes large quantities of unlabeled data and just a few labeled samples. Specifically, we first train a model on a large unlabeled dataset and then re-train the model with a few labeled data on the target classification problem.
2. We study three different sampling methods on the encrypted traffic classification problem: Fixed step sampling, random sampling, and incremental sampling. We show that good sampling methods can almost achieve the upper-bound accuracy in certain datasets.
3. We evaluate the proposed approach using captured QUIC traffic and show that our semi-supervised approach using sampled time series features can accurately classify QUIC traffic that has fewer unencrypted fields during handshake.
4. We test our approach on different public datasets. Surprisingly, we show that we can train a model using a completely separate unlabeled dataset and then retrain the model with a small number of labels in the target dataset and still achieve good accuracy.

2 RELATED WORK
Several recent studies have developed deep learning models, such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), for network traffic classification in a fully-supervised fashion. In [19], authors trained six different CNN models based on LeNet-5 model on an old public dataset with 12 classes. They converted 249 statistical characteristics into a 2-d 16×16 image and reported high accuracy. In [11], authors used CNN, LSTM and various combinations of them on a private dataset captured at RedIRIS, a Spanish academic and research backbone network. They used time series features of the first 20 packets, including source port, destination port, payload size, window size, etc.

In [12], a framework comprising a CNN and Stacked Auto-Encoder (SAE) was trained on a dataset containing 12 VPN and non-VPN traffic classes. They used raw header and payload bytes as input. Although no class labels are needed during the first step of training SAE, in the fine-tuning step they re-trained SAE in a supervised fashion with the entire dataset. In [2], Reproducing Kernel Hilbert Space (RKHS) was used to convert the time series features of a flow to an image. Then, produced images were used as input to a CNN mode. Their dataset is private and contained 5 application and protocol classes.

The only study that investigated QUIC protocol is [16]. They captured five Google services: Google Hangout Chat, Google Hangout Voice Call, YouTube, File transfer, and Google play music. They used CNN model and reported high accuracy. They captured 150GB of data and trained the model in a fully-supervised manner.

A survey paper [14] presents a general framework, covering all previous deep learning-based traffic classifiers, was introduced that can deal with any typical network traffic classification task. The paper provided a seven-step training process, including data capturing, data pre-processing, model selection and evaluation, etc. The framework also assumes large enough dataset for training.

In summary, in comparison, all work discussed above assumes large quantities of labeled data. Furthermore, packet sampling is not considered in their approaches.

In [9], authors used co-training method where two learners are trained iteratively on each other’s output to be able to cover the entire unlabeled dataset. To start the training process, a few labeled samples are needed for the first (source) learner to be trained on. Two datasets of different app configuration used for the first and second (target) learner. They used Random Forest (RF) and AdaBoost with decision tree as learners.

Their approach, however, is different from ours in several ways. First, co-training needs labeled data from the source task whereas our approach needs labeled data from the target task. As a result, in their approach, the number of classes and the corresponding names should be known for the target task for which no labeled data is needed. In contrast, we can use any unlabeled dataset without knowing anything about in our approach. Second, their co-training will only work when the source and target tasks are similar and share same labels while we have shown that our approach can be used as a general statistical feature estimator when unlabeled dataset does not contain target task traffic classes.

3 PROBLEM STATEMENT
As discussed earlier, deep learning models have been developed for (encrypted) traffic classification. Because deep learning approaches are capable of automatic feature selection and capturing highly complex patterns, they demonstrate high classification accuracy. However, a critical challenge is
that deep models require large amounts of labeled data during training. Capturing and labeling a dataset is a non-trivial and cumbersome process.

First, because encryption mechanisms are heavily used in today’s Internet, labeling a dataset captured in an operational network is almost impossible unless an accurate classifier is already available. As a result, labeling process is usually done by assuring that only one target class is available during capturing by turning off all other applications on the device used to generate traffic. This is also typically done in an isolated environment or at the edge of the network. Traffic distribution in such an environment could differ from an operational network, especially at the core of the network. In addition, to capture large amounts of labeled data used in literature, one often runs scripts to automatically perform certain actions that can be captured and labeled without manual labor. However, we will show that network traffic generated by scripts may have a different distribution from that of human-generated traffic and, consequently, a model trained on script-generated traffic may not be accurate on human-generated traffic in inference time.

In contrast, unlabeled data is abundant and readily available in an operational network. Capturing a large unlabeled dataset is an easy task. There are also many large and publicly available datasets. Hence, our objective is to use easily-obtainable unlabeled datasets to significantly reduce the size of labeled dataset needed for training an accurate traffic classifier.

Specifically, we hope to classify a number of traffic classes, called the target task. We only have a few labeled samples for each class that we are interested in. We call this dataset $D_1$. At the same time, we assume we have a large unlabeled dataset $D_u$, say with hundreds of thousands of flows. This unlabeled dataset $D_u$ may contain numerous flows from various traffic classes, even from classes that we are not interested in, i.e. they do not exist in $D_1$. The goal is to leverage the two datasets to train a traffic classification model for a target task while heavily exploiting $D_u$ dataset for training.

4 METHODOLOGY

4.1 Key Components

Our objective is to obtain an accurate traffic classifier with only a small number of labeled samples from each traffic class. To achieve this objective, we propose a semi-supervised learning approach. There are three key components in the proposed scheme.

The first is the classification model trained through semi-supervised learning. Specifically, we pre-train a model with $D_u$ and then transfer the model to a new architecture and re-trained the model with $D_l$. This is called semi-supervised learning. This approach considerably reduces the number of labeled data needed for the second supervised learning part. Moreover, the pre-trained model can be reused for other network traffic classification tasks.

In order to use an unlabeled dataset, $D_u$, we pre-train a model, $F$, such that it does not need human labor for labeling. We used pre-training and re-training to distinguish between the first and second step of our semi-supervised approach. An important step in the pre-training stage is to decide the target of the regression function. We choose a set of statistical features for this purpose. Moreover, the input of the model is a set of packets sampled from the entire flow. For each packet, we only observe length, direction, and relative time. In other words, $F$ is pre-trained to estimate statistical features of the entire flow by taking a set of sampled packets as an input. Hence, $F$ can be used for any other dataset for which statistical features give good classifier. The idea is based on the assumption that not all traffic patterns are valid and a model pre-trained on a large unlabeled dataset will lay on a manifold of valid patterns and hopefully can estimate statistical features.

Next, the pre-trained model, $F$, will be used as a part of another model, $G$. Then, $G$ will be re-trained with a small labeled dataset. Since a part of the model has already observed many traffic patterns, $G$ needs considerably less human-labeled data. Note that $F$ might not necessarily be an accurate estimator of statistical features. But, it will be re-trained quickly to help the classification task since it has already seen numerous traffic patterns during the pre-training.

The second key component is the features, including input features and the pre-training targets. As it is categorized in [14], there are three input features heavily used for network traffic classification tasks: time series features (such as packet length and inter-arrival time), statistical features obtained from the entire flow (such as average packet length and average byte sent per second), and header/payload features (such as TCP window size field, TLS handshake data fields and data content). Header/payload data features have been used for classification of encrypted traffic such as TLS 1.2 [12, 15]. These methods rely upon unencrypted data fields or message types exchanged during handshake phase of TLS 1.2. However, state-of-the-art encryption protocols, such as QUIC and TLS 1.3, aim to reduce the number of handshake messages to improve the speed of connection establishment. As a result, fewer unencrypted data fields and packets are exchanged in these protocols that makes it harder for header/payload based approaches to achieve high classification accuracy. Furthermore, statistical features require the model to observe the entire flow before classification which is not efficient in practice. However, statistical features present useful information of flows, and thus we use statistic features as the target in the pre-training stage.
The third key component of our approach is sampling. As discussed earlier, statistical features and header/payload features have their limitations. Therefore, we aim to use time series features. Specifically, we use time series features of only a part of a flow as an input to predict the statistical features as a regression target. Additionally, instead of using only the first few packets, which is used in most studies based on time series features [2, 3, 11], we sampled a fixed number of packets from a flow for the input. First, in practice, sampling is the only practical solution in some scenarios, such as in high bandwidth links or data centers. Moreover, sampling obviates the need to start capturing from the beginning of a flow or capturing the entire flow. Furthermore, storing the entire flow needs a large amount of memory and a model trained on would be more complex. Second, it allows the model to capture patterns from different part of a flow, not just the beginning of a flow. The approaches that used the first few packets can only capture specific patterns taken place at the beginning of a connection. However, these patterns may not necessarily be distinguishable from one class to another. For instance, user-specific behaviors, such as changing the quality of Youtube video, renaming a file in a Google Drive, etc., are mostly performed at the middle of a flow, not within the first few packets. Third, it allows us to sample a single flow several times which can serve as a data augmentation method.

In this paper, we propose a method to use time series features available regardless of encryption mechanism. We show that time series features can be used to classify services that use QUIC protocol. Moreover, only a small number of sampled packets are used for classification instead of the entire flow that reduces the memory and computational cost. To make sure that our approach can be used as a general framework, we also test our approach on two public datasets.

### 4.2 Semi-supervised Learning

#### 4.2.1 Convolutional Neural Networks

We used Convolutional Neural Network (CNN) as a part of our model. CNN is a type of neural networks commonly used for visual recognition tasks [10]. Traditional feed-forward neural networks are hard to train due to large number of learnable parameters when the input dimension is large. CCN mitigates this problem by sharing a set of small filters covering the entire receptive fields.

Similar to other neural network models, CNN consists of an input layer, an output layer and multiple hidden layers, as shown in Figure 1. Hidden layers can be convolutional layer, pooling layer, or fully connected layer. In convolutional layer, a set of learnable kernels (or filters) are used. These kernels are considerably smaller than the entire input, but they are used along the width and height of the input image to cover the entire input. By using the same set of small kernels over the entire input, the number of learnable parameters decreases such that it can be trained with reasonable memory and computational budget. Additionally, it allows the model to be shift invariant, that is, a pattern can be captured by CNN even if it is shifted to another region of input.

Pooling is another important layer in CNN which allows down-sampling. Pooling layers are usually used after a few convolutional layers as a form of non-linear down-sampling. There are several pooling layers, but max pooling is the most prevalent one. In max pooling, the maximum value of a set of adjacent neurons is used as a down-sampled output. Typically, after a set of convolutional and pooling layers, a few fully connected layers are used. These layers are responsible for high-level reasoning and associating captured patterns by previous layers with target class labels.

#### 4.2.2 Proposed Architecture

We used CNN as a part of the model architecture because of its shift invariant feature. Recall that we used sampled packets as an input to the model and as a data augmentation technique we sampled multiple times from different part of the flow. Hence, same set of patterns may be observed in different part of the input. Hence, the shift invariant model is more suitable.

As shown in Figure 2, a CNN-based model is first pre-trained with an unlabeled dataset. Then, the learned weights of the convolutional layers are transferred to a new model with more linear layers. Finally, the new model is re-trained on a small labeled dataset. The details of the model structure

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1. Note that we have tried several auto-encoder architectures to reconstruct the input or predict the future for the pre-training stage with the entire flow or first few packets. But, none of them actually worked.
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Sampled data from unlabeled dataset

Extracted statistical features

Sampled data from labeled dataset

Traffic classes

First Step (pre-training)

Second Step (re-training)

Conv1
Conv2
Pool3
Conv4
Pool5
Conv6
Conv7
Pool8
Conv8
Softmax

Table 1: Structure of the CNN model

|               | Conv1 | Conv2 | Pool3 | Conv4 | Pool5 | Conv6 | Conv7 | Conv8 |
|---------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Number of filters/neurons | 32    | 32    | -     | 64    | -     | 256   | 128   | 128   |
| Kernel size   | 5     | 5     | 3     | 3     | 3     | -     | -     | -     |

is presented in Table 1. We used max pooling and Rectified Linear Unit (ReLU) activation function. Batch normalization is also used after convolutional and max pooling layers.

The input of the model is a 1-dimensional vector with 2 channels. The first channel contains inter-arrival time of sampled packets and the second channel contains the packet length and direction combined. To compact the input data as much as possible, positive values of length represent the length of packet for forward direction and negative values represent the length for backward direction. Moreover, we normalized the input data range in [-1,+1] by considering the maximum value of 1434 Bytes and 1 second for length and inter-arrival time.

4.3 Sampling Techniques

In this paper, we used 3 different sampling methods to examine whether type of sampling affects performance of the traffic classification task.

- Fixed step sampling: In fixed step sampling, a fixed number, \( l \), is chosen and only packets that are \( l \) packets away from are sampled
- Random sampling: This technique simply samples each packet with probability \( p=1 \). This is a common technique in operational networks with high bandwidth
- Incremental sampling: Incremental sampling has three parameters, \((l, \alpha, \beta)\). Similar to fixed step sampling, it samples packets that are \( l \) packets away from, but it increases the value of \( l \) by multiplying it by \( \alpha \) after sampling each \( \beta \) packets.

During data augmentation, we sampled a flow 100 times from the beginning of the flow when random sampling was used. However, it would have given us the same set of packets if we had started from the beginning of a flow multiple times when using fixed step or incremental sampling. Hence, we started sampling at different part of a flow 100 times, if the flow was long enough.

4.4 Datasets

As explained earlier, our semi-supervised approach needs an unlabeled dataset for the pre-training stage and a labeled dataset for the re-training stage. In this paper, we conducted experiments with three datasets:

4.4.1 QUIC Dataset. This is a dataset captured in our lab at UC Davis and contains 5 Google services: Google Drive, Youtube, Google Docs, Google Search, and Google Music [5]. We used several systems with various configurations, including Windows 7, 8, 10, Ubuntu 16.4, and 17 operating systems with Chrome browser. We wrote several scripts
using Selenium WebDriver [18] and AutoIt [1] tools to mimic human behavior when capturing data. This approach allowed us to capture a large dataset without significant human effort. Such approach has been used in many other studies [3, 8, 16]. Furthermore, we also captured a few samples of real human interactions with Google services to show how much the accuracy of a model trained on scripted samples will degrade when it is tested on real human samples.

During preprocessing, we removed all non-QUIC traffic. We also ignored short flows because when short flows are sampled, there will not be enough packets to feed a classifier. In our evaluation, short flows are those with less than 100 packets before sampling. Note that all flows in our dataset are labeled, but we did not use class labels during the pre-training step. We used class labels of all flows to show the accuracy gap between a fully-supervised approach and our semi-supervised framework.

4.4.2 Unlabeled Waikato Dataset. WAND network research group at the university of Waikato published several unlabeled traces from 2009 to 2013. One of the most recent dataset that we used in this paper is Waikato VIII [6] captured at the border of the University of Waikato. The entire dataset is unlabeled and it is not clear what traffic classes exist in the dataset. However, the dataset definitely do not contain QUIC traffics because it was captured before the emergence of any practical implementation of QUIC protocol. We used Waikato dataset to pre-train a network that we later re-trained on QUIC and Ariel datasets.

Similar to QUIC dataset, all small flows were removed during preprocessing. Moreover, the dataset is extremely large and due to the limited time and computational budget, we only used traces of the first month which is around 4% of the entire dataset.

4.4.3 Ariel Dataset. Ariel dataset [4] was captured in a research lab at Ariel university over a period of two months. The original paper [13] used a fully-supervised method to classify three category of class labels: operating system, browser, and application. However, only the operating system and browser labels are available in the public dataset. Similar to other datasets, we removed all short flows. In this paper, we only used a small portion of the dataset to re-trained a pre-trained model to test our methodology.

5 EVALUATION

5.1 Implementation Detail

We used python and implemented the CNN architecture using PyTorch. We used a server with Intel Xeon W-2155 and Nvidia Titan Xp GPU using Ubuntu 16.04. The architecture of the CNN model has already been explained in section 4.2.2. During the pre-training, we trained the model with Adam optimizer and MSE loss function for 300 epochs. We used 24 statistical features as targets of regression. We used minimum, maximum, average, and standard deviation of packet length and inter-arrival time. For each one, we considered forward, backward and both flow directions that gave us a total of 24 features. During the supervised re-training, we used Adam optimizer with cross-entropy as a loss function.

5.2 Performance Metrics

There are two category of performance measures to evaluate a classifier: macro-average and micro-average metrics [17]. Whenever the accuracy of the entire model is shown, we used macro-averaging where the accuracy is averaged over all classes. For pre-class performance evaluation, we used micro-averaging metrics, including accuracy, precision, recall, and F1, as follows:

\[
\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (2)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (3)
\]

\[
F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)
\]

In the above equations, TP, FP, TN, and FN stand for True Positive, False Positive, True Negative, and False Negative, respectively.

5.3 QUIC Dataset

We first pre-train our model on QUIC dataset consisting of 6439 flows without using class labels. Recall that because we sample each flow up to 100 times, total number of samples during the training is 544744. We use 24 statistical features calculated from flows as regression targets. Then, we transfer the weights to a new model and re-train with class labels. For this step, we capture 30 flows for each class and divide the training and test with different number of flows. We also perform cross-validation. Moreover, we train the same model without transferring the weight to show the performance gap.

To find a good parameter for the sampling methods, we separate 30 files for each class and conduct greedy search. We train the model only with 20 labeled flows and test with other 10 flows. This small number of training data does not probably gave us the optimal parameters, but we assume

\[\text{Semi-supervised-Learning-QUIC-}\]

\[\text{3 Our code is available at https://github.com/shrezaei/}
\]

\[\text{4 In the entire paper, we use flow to refer to an unsampled flow and we}
\]

\[\text{use sampled flow for the sampled case. In other words, a dataset with 30}
\]

\[\text{flows per class contains up to 3000 sampled flows per class because each}
\]

\[\text{unsampled flow is sampled multiple times.}\]
that only limited labeled data is available for any supervised training we conduct. The parameters we use for fixed sampling, incremental sampling and random sampling are 22, (22, 1,6, 10), and 1/22, respectively. We also sample only 45 packets from the entire flow.

Figure 3 presents the accuracy of our model with various settings. It shows that increasing the size of the training set improves the accuracy except for random sampling. The reason is that during random sampling, we always started sampling from the beginning of the flow each 100 times we sampled a flow. Hence, the data augmentation method with only 5 files gives the model enough data to capture the patterns corresponding to the beginning of the flow. However, the accuracy of random sampling barely increases when increasing training size. We conjecture that this is because imposing randomness during random sampling makes it more difficult for the model to fit to the true distribution. Fixed step and incremental sampling methods dealt with sampled flows captured from different part of flows. Therefore, if different part of flows shows different patterns, data augmentation of these two methods does not necessarily give more samples for each pattern. Hence, increasing the training size boosts the accuracy.

As shown in Figure 3, incremental sampling outperforms other sampling methods. When random or fixed sampling is used, it is not easy to capture both long and short patterns. Incremental sampling allows sampled flows to contain many packets in short range and some packets in long range. That is why incremental sampling outperforms other sampling methods when transfer learning is used. Furthermore, the figure clearly shows the efficacy of our transfer learning model on fixed step and incremental sampling, as expected. Our method improves the accuracy around 10% when compared with a model without the pre-training step.

| Supervised training size | Fixed step | Random | Incremental |
|-------------------------|------------|--------|-------------|
| 20 flows per class      | 94.60%     | 91.35% | 98.53%      |
| Entire dataset          | 96.50%     | 96.92% | 98.99%      |

Table 2 represents the accuracy of CNN model when the entire labeled dataset is used in a supervised manner. In that case, we do not conduct the first step pre-training because all the dataset was used to train the second model. This gives us the upper-bound for the accuracy of a fully-supervised learning when sampling is used. The accuracy of incremental sampling is close to the upper-bound when only 20 flows per class was used for re-training. But, fixed sampling and random sampling require larger labeled training set during the re-training. To find how much sampling degrades accuracy, we also train a Random Forest (RF) classifier that takes statistical features as input and predicts the class labels. The accuracy of RF was 99.87% which shows that sampling degrades performance up to around 4% for our dataset. Note that we deliberately avoid using deep models such as CNN for this part because the input is a set statistical features which is not suitable for a shift-invariant model, such as CNN. Fully connected neural network is also unnecessarily complex to be trained with our relatively small dataset. Note that our dataset has only around 6500 flows. When using statistical features as an input, it is not possible to augment the dataset. As a result, total number of data points used during training RF was around 100 times fewer than training a model with sampled data.

In the second experiment, we study the effect of number of sampled packets on the accuracy of the model. We change the number of sampled packets from 30 to 75. We set the parameters of fixed step sampling method so that it always covers around the range of 1000 packets. Interestingly, the accuracy drops when we increase the number of sampled packets, as shown in Figure 4. Increasing the number of sampled packets improves the accuracy of statistical feature prediction. However, it is harder for the model to learn class labels when input dimension is larger because of the small training set.

Figure 5 presents the performance metric of our best model, that is, a model re-trained on a pre-trained model using 20 training flows with incremental sampling. The high performance metric shows that it is possible to train a good classifier with as small as 20 flows for each class if our semi-supervised approach is used. Therefore, it dramatically reduces the data collection and labeling that are the most time-consuming and labor-intensive steps.
To study whether automatically generated data with script represents human interaction, we capture 15 flows for each class from an interaction of real human in those 5 Google services. We only use this dataset to test the same model described above. Figure 6 illustrates the performance metrics of all classes. Interestingly, accuracy of the Google search and Google document have not changed significantly. However, the accuracy of Google drive, Youtube, and Google music drop up to 7%. This depends on how much human interactions can change the traffic pattern, which is class-dependent. Moreover, there are some actions, such as renaming a file or moving files in Google drive, that our scripts do not perform. So, these patterns are not available during re-training. This shows the limitations of dataset and studies [3, 8, 16] that only use scripts to mimic human behavior.

QUIC protocol has been only developed and used recently. Therefore, Waikato dataset captured before 2014 cannot have QUIC protocol traffic. Our intuition is that a model pre-trained on Waikato dataset can still be useful for the re-training step because it basically learned how to predict statistical features. It can be considered as a naive statistical feature predictor based on sampled data. Table 3 presents the accuracy of our method when Waikato dataset is used for pre-training. Note that sampling method’s parameters are different for this experiment. Waikato dataset has many small flows that are not suitable for our previous sampling parameters that covers around 1000 packets. Hence, we change the parameters of sampling methods, similar to the parameter used in next section. That is the reason why the accuracy of even model without pre-training is lower than the experiment shown in Figure 3. Table 3 clearly shows that the pre-trained model can boost the accuracy even when it had not seen any traffic of the target task during the pre-training stage. But, the improvement is limited to less than 10% in this case.

### 5.4 Ariel Dataset

We conduct two additional experiments to evaluate the performance of our semi-supervised learning method on public datasets. In the first experiment, we pre-train a model with the unlabeled Waikato dataset to predict statistical features based on sampled flows. Then, we re-train the model with 5 flows of each class in Ariel dataset. We randomly select 5 flows without pre-training and 20 flows with pre-training. Figure 4 illustrates the effect of number of samples in fixed step sampling on accuracy.

![Figure 4: Effect of number of samples in fixed step sampling on accuracy](image)

Table 3: Accuracy of QUIC dataset with different sampling methods when pre-trained on Waikato dataset

| Pre-trained on Waikato | Fixed step | Random | Incremental |
|------------------------|------------|--------|-------------|
| No                     | 74.51%     | 72.14% | 74.35%      |
| Yes                    | 81.50%     | 81.27% | 80.76%      |
We deliberately allow the combined dataset to remain imbalanced to mimic real scenarios where only small portion of unlabeled dataset contains the target labels. Additionally, the parameters we use for fixed sampling, incremental sampling and random sampling are 10, (8, 1, 2, 10), and 0.15, respectively.

The accuracy of both experiments as well as the one without semi-supervised learning is shown in Table 4. For brevity, we represent Waikato and Ariel datasets with W and A, respectively. When there is no pre-training, random sampling shows the best accuracy. The similar trend is observed with our QUIC dataset as well, in previous section. Interestingly, there is a small but meaningful gap between the two experiments. That shows that even if the target classes are only a small portion of dataset during the pre-training step, they can improve the accuracy. This is useful because the percentage of target task’s flows might be probably small in real word when data is captured from an operational network.

To measure the performance gap between semi-supervised and fully-supervised learning, we also train the same CNN-based architecture with the entire Ariel dataset in a fully-supervised manner. First, we train the CNN model with augmented sampled flows from Ariel dataset using fixed step sampling. As it shown in Figure 7, the accuracy is around 89% which can be considered as an upper-bound when sampling is used. To compare how statistical feature prediction degrades the accuracy in comparison with using true statistical features, we perform the following experiment: We feed the true statistical features to the last three layers of the model directly and remove all previous layers. However, the training phase is extremely unstable and high variance with low accuracy. The main reason is that several dense layers of fully connected neural network is too complex to be trained with a small dataset. Recall that when we do sampling, we can sample a single flow multiple times which increases the dataset size. However, in the case of feeding the true statistical features, there is only one set of statistical features for each flow leading to small size dataset. Therefore, we use K-Nearest Neighbor (KNN) for a fully-supervised training with statistical features.

The performance gap is shown in Fig. 7. We only show results of the fixed step sampling. The trend of other sampling methods are similar when number of flows for the supervised re-training increased. Interestingly, if a pre-trained model contains the target class labels, it can reach the upper-bound accuracy (fully supervised with sampled flows) with only around 30 labeled flows for each class. This is dramatically smaller than typical datasets used for fully-supervised methods in literature. Moreover, even if the unlabeled dataset does not contain target task’s flows, the pre-trained model can act as a general function approximation of statistical features because it has already observed a large number of samples during the pre-training step.

6 DISCUSSION

Typically, network traffic classifiers use one or combination of the following features [14]: statistical features, time series, and header/payload contents. The choice of input features depends on many factors, which are comprehensively explained in [14]. During the pre-training step, our approach uses sampled time series features and outputs statistical features. Hence, our approach does not work on datasets for which time series or statistical features are not good enough.

Table 4: Accuracy of Ariel datasets with different sampling methods and pre-training configurations

| Pre-trained on Sampling | Fixed step | Random | Incremental |
|-------------------------|------------|--------|------------|
| -                       | 53.37%     | 70.76% | 40.37%     |
| W                       | 79.76%     | 75.65% | 80.82%     |
| W+A                     | 81.66%     | 78.54% | 84.53%     |

5 The reason we do not perform cross-validation is that if we limit each training folds to only contain 5 flows, the total number of cross validation rounds would be too large to be practically evaluated.

6 It has shown that it is possible to get a better accuracy with Ariel dataset using some other statistical features [13]. But, we use the same statistical features that we used as regression targets during the pre-training step to have a fair comparison.

Figure 7: Effect of labeled dataset size on accuracy
for classification. For instance, we also conducted an experiment on ISCX dataset [7] for which the accuracy of model based on statistical and time series features were reported to be around 80% [7]. Our approach failed to produce a model with higher than 68% accuracy when only 20 flows were used from each class during the supervised re-training step. However, a CNN model using payload information achieved above 95% accuracy on the same dataset with fully-supervised learning in [12].

During the pre-training step, the model will probably see most possible traffic patterns, even the patterns that are not similar to any of the target classes. However, it is possible that during the supervised re-training step, some distinctive patterns are missed from labeled dataset which degrades the accuracy dramatically if the model is used in real environment. Hence, the small labeled dataset should be captured carefully. For instance, it has been shown that user actions in certain Android applications, such as Facebook or Twitter can be identified using time series features [3]. These actions are sending message, posting status, opening the application, etc. This means that if target classes are Android applications, one should ensure that all actions are included in the small labeled dataset at least once because the pattern of action is different from another. This is similar to the experiment we did to test our model on human-triggered data where we realized some actions in some Google services did not exist in our training set, such as renaming a file in Google Drive.

We show that incremental sampling outperforms other sampling methods. However, it should be used with caution. Recall that we use CNN model for classification. CNN uses a set of kernels (or filters) to cover the entire input. In incremental sampling, the sampling parameter l is increased by α after sampling each β packets. If one chooses a large value for α, distance between the first few sampled packets are significantly smaller that the last few packets. In that case, CNN model is not suitable because the same filter which is supposed to capture certain pattern for close sampled packets will be used on the last few packets which are far away from. Hence, when using incremental sampling, one should not use large α. Otherwise, CNN model will fail to work properly.

7 CONCLUSION

In this paper, we propose a semi-supervised learning method that reduces the number of labeled data significantly for network traffic classification. We use 1-D CNN model that takes sampled time series features as input. Hence, the method is also suitable for scenarios in which only sampled data is available, such as in high-bandwidth links. In the pre-training step, the model is trained to predict statistical features of the entire flow, which does not require human effort for labeling. The main idea is to pre-train a model on a large unlabeled dataset and then transfer the learned parameters to a new model and re-train it with a very small labeled dataset. We capture 5 Google services that use QUIC protocol to evaluate our model. We show that with the proposed semi-supervised learning approach and 20 labeled data from each class the model achieves high accuracy close to a model trained on a large labeled dataset with certain sampling methods. We evaluate 3 sampling methods: fixed step, random, and incremental sampling.

We also conduct experiments on public datasets to show the generalizability of the proposed approach. We use the publicly available Waikato and Ariel datasets. We show a model pre-trained on Waikato dataset can improve the accuracy of Ariel dataset when the pre-trained model is transferred. This shows that a model pre-trained with our approach on a large unlabeled dataset can be used as a general traffic classifier that can improve the accuracy of probably any traffic classification tasks if weights are transferred. In addition, while the pre-training can take a relatively long time, the retraining process can be rather fast. Such evaluations demonstrate the efficacy of the proposed approach.

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