Multitask Learning for Network Traffic Classification

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ABSTRACT
Traffic classification has various applications in today’s Internet, from resource allocation, billing and QoS purposes in ISPs to firewall and malware detection in clients. Classical machine learning algorithms and deep learning models have been widely used to solve the traffic classification task. However, training such models requires a large amount of labeled data. Labeling data is often the most difficult and time-consuming process in building a classifier. To solve this challenge, we reformulate the traffic classification into a multi-task learning framework where bandwidth requirement and duration of a flow are predicted along with the traffic class. The motivation of this approach is twofold: First, bandwidth requirement and duration are useful in many applications, including routing, resource allocation, and QoS provisioning. Second, these two values can be obtained from each flow easily without the need for human labeling or capturing flows in a controlled and isolated environment. We show that with a large amount of easily obtainable data samples for bandwidth and duration prediction tasks, and only a few data samples for the traffic classification task, one can achieve high accuracy. We conduct two experiment with ISCX and QUIC public datasets and show the efficacy of our approach.

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

KEYWORDS
Multitask Learning, Supervised Learning, Network Traffic Classification, QUIC Protocol Classification

1 INTRODUCTION
Network traffic classification has a wide variety of applications in today’s Internet, such as resource allocation, QoS provisioning, pricing in ISPs, anomaly detection, etc. The earliest approaches to solve network traffic classification used port numbers or unencrypted packet payloads. These methods relied on human labor for continuously finding patterns in unencrypted payloads or matching port numbers. Due to inefficiency and lack of accuracy, new methods based on classical machine learning algorithms emerged, such as such as random forest (RF) and k-nearest neighbor (KNN).

For several years, classical machine learning algorithms had achieved state-of-the-art accuracy in the traffic classification task. However, these relatively simple methods were not able to capture more complex patterns which exist in today’s Internet traffic and, therefore, their accuracy has degraded. Recently, deep learning models achieved the state-of-the-art performance in traffic classification.

Their ability to learn complex patterns and perform automatic feature extraction makes them desirable for traffic classification.

Although deep learning methods can achieve high accuracy, they require a large amount of labeled training data. In the network traffic classification task, labeling is a time-consuming and cumbersome task. In order to correctly label each flow, researchers usually capture flows of each class in isolation and in a controlled environment with minimum background traffic. This process is very time-consuming. Moreover, traffic patterns observed in a controlled environment might be greatly different from real traffic, which makes the inference inaccurate.

To mitigate the need for a large amount of labeled training samples, we propose a multi-task learning approach which performs three predictions (tasks), for which only one requires human effort and controlled environment for labeling. These tasks are bandwidth, duration, and traffic class prediction tasks. For any captured data, whether it is captured in a controlled environment in isolation or not, one can easily compute the total bandwidth and duration of each flow without human labor. Hence, by formulating the traffic classification problem in a multi-task learning framework where the large amount of model parameters are shared among all tasks, one can train the model with a large amount of data for bandwidth and duration tasks and only a small number of labeled samples for traffic class prediction task. Moreover, for various applications, such as resource allocation or QoS purpose, bandwidth and duration prediction is highly useful.

2 RELATED WORK
Before the widespread emergence of deep learning models, classical machine learning approaches have been widely used for network traffic classification [7]. These methods usually relied on supervised learning methods, such as support vector machine (SVM) [8, 9], C4.5 [10, 11], naive Bayes [12, 13], k-nearest neighbor (KNN), etc., or unsupervised clustering methods, such as k-means [16, 17] or Gaussian mixture model [18]. However, their accuracy has declined recently due to the simplicity, manual feature extraction (which becomes more difficult with today’s strongly encrypted traffic), and the lack of high learning capacity to capture more complex patterns.

In the past few years, with the promising success of deep learning methods on variety of problems, such as image classification, voice recognition, translation, etc., network researchers recently adopted these methods for traffic classification [6]. In [20], a LeNet-5 CNN model, designed in 1998 for handwritten numeral recognition, is used for traffic type classification. Numerous statistical features are rearranged into a 2-dimensional image as input to the model. They report high accuracy, but the model cannot be used for online applications [4] because it requires an entire flow to be observed to obtain the statistical features. In [21], authors use both statistical features and payload data for traffic classification of
QUIC protocol. They first use statistical features with random forest algorithm to distinguish between chat and voice call with other classes. If other classes are detected, they use payload data with a CNN model to classify video streaming, file transfer, and Google music. Their first stage needs the entire flow to be observed and, hence, it is only suitable for offline applications. Using payload information, although encrypted, has been used in other papers as well. In [23], a CNN and stacked Auto-Encoder (SAE) are used together on ISCX dataset to classify traffic types and applications. These methods use deep neural networks as a black box without identifying human understandable features.

In [22], time-series features of each flow are converted into 2-dimensional images using Reproducing Kernel Hilbert Space (RKHS). The produced images are used as input to a CNN model. They compare their CNN model with classical machine learning approaches, including SVM, decision tree and naive Bayes. The CNN model achieve over 99% accuracy and outperforms classical machine learning approaches. In [19], a convolutional neural network, a long short-term memory (LSTM) model and various combinations are used for classification of several services, such as YouTube and Office365. They achieve the accuracy of around 96% when time-series features and header features are used with the CNN/LSTM architecture. In [4], a general framework is proposed providing a straightforward guidelines and directions for any traffic classification task. Most previous work falls under the general framework. However, all these methods rely on supervised learning and require a large amount of labeled data for training. This becomes more problematic for deep models because they need significantly more training data than classical machine learning approaches.

The only study that addresses the need for a large labeled dataset is [3]. This approach consists of a semi-supervised learning method, where a CNN model is first pre-train to predict several statistical features from the sampled packets. They use time-series features of sampled packets. Then, they replace the last few layers with new ones and then re-train with a small labeled dataset. The advantage of their approach is that it does not need human effort for labeling the pre-trained dataset because statistical features can be computed easily when entire flows are available. However, their approach takes sampled data packets which means that it needs to observe a large portion of a flow before performing the classification which is not suitable for online applications. In this paper, we propose a multi-task learning approach that outperforms both single-task learning and transfer learning.

3 METHODOLOGY

3.1 Motivation

This paper is motivated by the following observations: First, it is difficult to obtain sufficient labeled training data for traffic classifications. At the same time, there are other prediction tasks (other than traffic classification) that are needed for resource allocation and have easy-to-obtain labels. Therefore, we are motivated to solve the two problems together through multi-task learning.

First, capturing a large enough labeled dataset for traffic classification to train a deep model is a time-consuming and cumbersome task [4]. Moreover, correctly labeling captured data is also challenging, particularly when background traffic or more than one traffic classes exist during capturing. On the other hand, unlabeled data is often abundant and easy to capture. Hence, it is desirable to be able to use a large amount of unlabeled data to dramatically reduce the number of labeled data needed for training. In this paper, we use a large unlabeled datasets with a small number of labeled data in a multi-task learning framework to solve this problem.

The second motivation of our approach is that ISPs or data centers often perform traffic classification for billing, resource allocation or QoS purposes. For such purposes, the traffic class along with other flow features, such as bandwidth requirement and duration, can significantly improve ISPs decision for resource allocation, QoS, etc. In this paper, we propose a multi-task learning approach that take the first few time-series features of a flow and perform three prediction tasks: bandwidth, duration, and traffic class. Not only the bandwidth and duration predictions are useful, they do not need human labor for labeling and one can capture a large amount of flows and then compute the bandwidth and duration of them easily.

3.2 Input Features and Prediction Outputs

In general, modern network traffic classifiers use one or combination of four categories of input features: time-series, header, payload, and statistical features [4]. Header information is rarely used nowadays since it does not achieve acceptable accuracy. Statistical features are obtained from the entire flow and, consequently, is not suitable for online classification where the prediction is needed as soon as traffic emerges. Online classification is necessary when resource allocation, QoS or routing decisions depend on the prediction output. Payload data has been shown to be useful for some datasets and special traffic types and encryption methods [5, 23]. The success of these methods stems from unencrypted fields during the handshake phase of TLS 1.2 [3]. However, modern encryption methods, e.g. QUIC and TLS 1.3, reduce the number of unencrypted fields as much as possible. Hence, for the new and stronger encryption protocols, payload information may not be as useful.

In this paper, we use three time-series features, that is, packet length, inter-arrival time, and direction, of the first \( k \) packets. The input of our model is a vector of length \( k \) with 2 channels. The first channel contains the inter-arrival time of the first \( k \) packets and the second channel contains the length and direction combined. As in [3], for the second channel, a positive value indicates the packet length in forward direction (from a client to a server) and a negative value indicates the packet length in backward direction. Moreover, we normalize the data by assuming a maximum value of 1434 Bytes for length and 1 second for inter-arrival time.

The common approach for traffic classification often focuses on predicting traffic types, applications, operating systems, user actions, etc. In addition to such class labels, we aim to predict duration and bandwidth requirements of traffic which can be used for resource allocation, routing, or QoS purposes. In this paper, we categorizes bandwidth and duration into five and four classes, respectively. In our experiment, the model takes long time to converge and does not perform well when bandwidth and duration tasks are defined as regression problems. In addition, coarse-grained predictions are often enough for routing or QoS purposes. Therefore, we reformulate these tasks as classification tasks. The bandwidth...
and duration class definitions are shown in Table 1. For example, if an entire flow bandwidth and duration is 53 kbps and 5 seconds, the corresponding bandwidth and duration class is 3 and 1, respectively. We define these classes in such a way that it is intuitive and each class covers a portion of our dataset. In our experiments, the performance of the model is not considerably affected by the small changes in bandwidth and duration class definitions.

In this paper, we use bandwidth and duration as tasks that do not need human effort for labeling and can be obtained easily in large quantities. One can also use other statistical features for such tasks, such as average packet length, standard deviation of inter-arrival time, etc., which are also used in the transfer learning approach in [3]. Such tasks can also improve model training. However, these prediction tasks do not have direct usage and can be considered as auxiliary tasks. Due to the lack of space, we only present the results of the model which predicts traffic class, bandwidth, and duration.

### 3.3 Multi-task Model Architecture

In this paper, we use 1-dimensional convolutional neural network (CNN) in our multi-task learning model architecture. CNN architecture was first introduced and used for visual recognition tasks. However, in the past few years it has been extensively adopted for various tasks in other fields. One of the most important features of CNN models is their shift invariance. These models basically contain a set of filters (kernels) in each convolutional layer that applies to the entire input and produces an output for the next layer. Since the same filter is applied to the entire input, patterns that are associated with that filter will be triggered regardless of their location in the input. This phenomenon, called shift invariance, is suitable for traffic classification task with time-series features because traffic patterns for each class may not necessarily appear in the same location in flows.

The overall architecture of our approach is shown in Figure 1. The details of the model parameters are presented in Table 2. We use max pooling as it is commonly preferred over other pooling methods. Rectified linear unit (ReLU) activation is also used as an activation function in the entire model, except the last layers which contain Softmax.

Suppose bandwidth, duration and traffic class prediction tasks are denoted by B, D, and T, respectively. Additionally, we have $N$ training data for which $x_i$ represents the input of $i$-th data sample and $y_i^B$, $y_i^D$, and $y_i^T$ represent the corresponding output for bandwidth, duration, and traffic class prediction tasks$^1$. The objective of the multi-task learning approach can be formulated as

$$\arg \min_{W^B, W^D, W^T} \sum_{i=1}^{N} \ell(y_i^B, f(x_i; W^B)) + \ell(y_i^D, f(x_i; W^D)) + \lambda \ell(y_i^T, f(x_i; W^T))$$

(1)

where $\ell$ is a cross entropy loss function. $\lambda$ is a weight that signifies the importance of the traffic class prediction task. Since this task has considerably fewer training data samples than the other two tasks, we can increase $\lambda$ to slightly compensate for the lack of labeled data. Note that for all training data, bandwidth and duration labels are available. However, only a small portion of data samples have traffic class labels. During training, we multiply the input of traffic class softmax layer to a mask vector to prevent back-propagation from this task for data samples that do not have a traffic class label.

### 3.4 Datasets

#### 3.4.1 QUIC Dataset. The QUIC dataset [3] is captured at university of California at Davis. It contains QUIC traffic of 5 Google services: Google Doc (1251 flows), Google Drive (1664 flows), Google Music (622 flows), Youtube (1107 flows), Google Search (1945 flows). The dataset contains time-series features: packet length, relative time, and direction. The dataset has already been pre-processed. According to [3], all short flows that have fewer than 100 packets had been removed. Note that all flows in the dataset are labeled. However, to evaluate our multi-task learning approach, we only use a small portion of class labels during training.

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$^1$ In this paper, scalar, vector, and matrix are denoted by lowercase, bold lowercase, and bold capital letter, respectively.
3.4.2 ISCX VPN-nonVPN Dataset. ISCX Dataset [1] is captured at University of New Brunswick and it contains raw pcap files of several traffic types. The dataset provides a fine-grained labels which allows different categorization: application-based (e.g. AIM chat, Gmail, Facebook, etc), traffic-type-based (e.g. chat, streaming, VoIP, etc), and VPN/non-VPN. In this paper, we divide the dataset into 5 categories that have different QoS requirements and bandwidth/duration characteristics: chat, email, file transfer, streaming, and VoIP. Both UDP and TCP traffic exist in the dataset. For TCP flows, we look for FIN packet to identify the end of TCP flows. For UDP flows, we use flow timeout of 15 seconds as in [2] to mark the end of UDP flows. Similar to the QUIC dataset, all flows are associated with a traffic type label, but we only use a small portion of labels for traffic class prediction of multi-task learning.

4 EVALUATION

4.1 Implementation Detail

We use python and Keras package to implement our multi-task learning approach\(^2\). We use a server with Nvidia Titan Xp GPU and Intel Xeon W-2155 with Ubuntu 16.04. We conduct experiments with both ISCX and QUIC dataset. In all of our experiments, the training phase took less than a few minutes. We use batch optimization and Adam optimizer for training. The loss function and model architecture are explained in Section 3.3.

4.2 QUIC Dataset

In this section, we compare the accuracy of our multi-task learning approach with transfer learning and single-task learning approaches. Table 3 shows the accuracy of these three approaches for QUIC dataset. For single-task learning, we use the same architecture as in Section 3.3, but with only one task-specific layer at the end. We train the model three times from scratch for each task. For bandwidth and duration prediction, we use the entire dataset for training since it does not require human effort for labeling. That is why the accuracy remain the same when labeled samples increased in Table 3. For transfer learning, we deploy an approach similar to [3] with slightly different source tasks. We first train the model with the entire dataset to predict the bandwidth/duration tuple. Then, we train the model for the traffic class prediction task. The final model only predicts the traffic class. That is the reason why Table 3 does not contain the bandwidth and duration accuracy for the transfer learning approach. Note that there is another difference between the transfer learning approach we use and the one proposed in [3]. In [3], the model takes sampled time-series features as input which is not suitable for online classification needed for resource allocation, routing, or QoS purposes. Therefore, we take the first \(k\) packets as input of the model. For multi-task learning approach, we train the entire model with all training data. We use the bandwidth and duration labels of the entire training data samples, while we only provide a limited number of labels for the traffic class task (specified in the first column). For this experiment, we set \(\lambda\) to one to emphasize on all three tasks equally. Moreover, we use the first 60 packets as input (\(k = 60\)).

As it is shown in Table 3, the accuracy of the traffic class prediction, for which we have limited labeled samples, is considerably higher with our multi-task learning approach than the transfer learning and single-task learning. In fact, the large amount of data that is available for bandwidth and duration tasks significantly improves the training process by allowing the model parameters to be trained with such abundant data. Although the transfer learning approach also reaps the benefits of the large dataset during pre-training, it is more prone to catastrophic forgetting [24], losing the ability to perform previous tasks, or over-fitting, losing the ability to generalize by fitting closely to a training dataset, particularly when the target task has a small number of training samples.

Note that the accuracy of a single-task learning is 96.67% when the entire dataset with all class labels are used. For traffic class prediction task, the multi-task learning approach with 100 labeled samples reach almost the same accuracy as single-task learning using the entire labeled dataset. Hence, the multi-task learning approach can greatly reduce the number of labeled data. There is no significant performance difference between single-task learning and multi-task learning for bandwidth and duration prediction tasks because there are abundant data samples for these tasks.

Figure 2 shows the accuracy of the multi-task learning approach for all three tasks when different number of packets are used as input\(^3\). Interestingly, bandwidth and duration can be predicted with as few as 30 packets and increasing the number of packets does not considerably improve the accuracy. For traffic classification task, there is a significant performance improvement from 30 to 60 packets. However, the traffic class prediction cannot get more accurate by observing more packets.

Figure 3 shows the prediction accuracy of the three tasks with different \(\lambda\). Intuitively, when training samples of one task is considerably smaller than other tasks in multi-task learning, the shared parameters are affected by tasks with abundant data during training. Hence, increasing the weight of the loss function of the task with fewer data, as it is explained in Section 3.3, may compensate for the lack of data during training and increase the effect of this task on training shared parameters. As shown in Figure 3, increasing \(\lambda\) helps the model to fit to the traffic class prediction tasks

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\(^2\) Codes are available at https://github.com/shrezacx/MultitaskTrafficClassification

\(^3\) Note that for the experiments with 30 and 45 packets, we removed one of the convolutional layers with 128 filters because that reduces the model input to a zero dimensional vector.

| Number of filters/neurons | Conv | Conv | Pool | Conv | Conv | Pool | Conv | Conv | Pool | FC | FC |
|----------------------------|------|------|------|------|------|------|------|------|------|----|----|
| Kernel size                | 3    | 3    | 2    | 3    | 3    | 2    | 3    | 3    | 2    | 256| 256|

Table 2: Structure of the CNN model
Table 3: Accuracy on QUIC dataset

| Number of labeled samples (For traffic class) | Single-task learning | Transfer learning | Multi-task learning |
|---------------------------------------------|----------------------|-------------------|--------------------|
| 10  [87.33%, 82.00%, 57.33%]               | [-, -, 85.33%]       | [88.67%, 81.33%, 90.67%] |
| 20  [87.33%, 82.00%, 58.67%]               | [-, -, 87.33%]       | [88.67%, 81.33%, 92.67%] |
| 50  [87.33%, 82.00%, 68.67%]               | [-, -, 90.67%]       | [89.33%, 80.67%, 94.67%] |
| 100 [87.33%, 82.00%, 78.67%]               | [-, -, 92.67%]       | [89.33%, 80.76%, 95.33%] |

Figure 2: Number of input packets versus accuracy for QUIC dataset

Figure 3: \(\lambda \) versus accuracy for QUIC dataset

as well until it reaches the maximum accuracy. However, increasing the \(\lambda\) further will hearth the accuracy of all tasks. That is because when \(\lambda\) is very large, the model highly over-fits to the traffic classification training data and, consequently, performs worse on test data of all tasks. Hence, for multi-task learning approach, one should find the suitable value of \(\lambda\) as a hyper-parameter.

4.3 ISCX Dataset

In this section, we use ISCX dataset and combine all classes into 5 different traffic types as explained in Section 3.4. Although it has been shown that a CNN model with payload information as input achieves higher accuracy for this dataset [23], we conduct experiments with ISCX dataset to only show the performance improvement of our multi-task learning approach over single-task learning and transfer learning approach in general.

Table 4 presents the accuracy of bandwidth, duration, and traffic class tasks for ISCX dataset. Regardless of the learning approach, the accuracy of traffic class task is lower in ISCX dataset (Table 4) than QUIC dataset (Table 3). Similar to Section 4.2, we set the \(\lambda\) to one and \(k\) to 60 packets. As shown in Table 4, the accuracy of bandwidth and duration tasks are similar for multi-task learning and single-task learning approaches. This suggests that patterns and convolutional filters that are suitable for bandwidth prediction are also suitable for duration prediction because in multi-task learning approach they shared the same model parameters and they achieve the same accuracy. The accuracy of the traffic class task is not as high as other tasks, but the table shows a significant improvement with multi-task learning approach in comparison with other approaches.

Figure 4 illustrates the accuracy of the three tasks versus the number of packets, \(k\). Unlike QUIC dataset, the duration task needs to observe more packets for accurate prediction. Bandwidth and traffic class prediction tasks show the same trend as QUIC dataset. Interestingly, both ISCX and QUIC datasets almost achieve their maximum accuracy for all their tasks with around 60 input packets.

Figure 5 shows the accuracy of all tasks when using different \(\lambda\). In this experiment, we use 20 labeled data samples per class (for traffic class prediction) and the entire dataset for bandwidth and duration tasks. Similar to QUIC dataset (Figure 3), the maximum accuracy of the traffic class prediction reaches around \(\lambda = 10\). Similarly, as in Section 4.2, by further increasing \(\lambda\), the model over-fits to traffic classification task which degrades the performance of all tasks.

5 DISCUSSION

In this paper, we use bandwidth and duration predictions as tasks with abundant training data. These two tasks have potential usage, as discussed earlier. However, for scenarios where these predictions are not important and they only serve to improve the accuracy of traffic classification, one can use other prediction tasks (e.g., average inter-arrival time or number of bursts) as auxiliary
work traffic flows. Since the bandwidth and duration tasks does not need labeling, a large amount of data can be easily captured and used for training these two tasks. We show that by providing a large enough amount of unlabeled data for bandwidth and duration tasks, one can train the traffic model with both unlabeled data and labeled data. If a pre-trained model is given without the training data, it obviates the need for a large amount of labeled data samples. Hence, it is desirable to avoid multi-task learning since it needs to train the whole model with both unlabeled data and labeled data. If a pre-trained model is available, transfer learning can train a model extremely fast, although using a public pre-trained model is shown to expose security threat [25].

### 6 CONCLUSION

In this paper, we propose a multi-task learning approach that predicts traffic class labels as well as bandwidth and duration of network traffic flows. Since the bandwidth and duration tasks does not require human effort or controlled and isolated environment for labeling, a large amount of data can be easily captured and used for training these two tasks. We show that by providing a large enough data for bandwidth and duration tasks, one can train the traffic class prediction task with only a small number of samples. Hence, it obviates the need for a large amount of labeled data samples for traffic classification. Moreover, bandwidth and duration predictions can be used for resource allocation, routing and QoS purposes in ISPs. We conduct experiments with two public datasets: QUIC and ISCX VPN-nonVPN. We illustrate that our multi-task learning approach significantly outperforms both single-task and transfer learning approaches.

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