Deep Learning based Traffic Classification – Further investigation

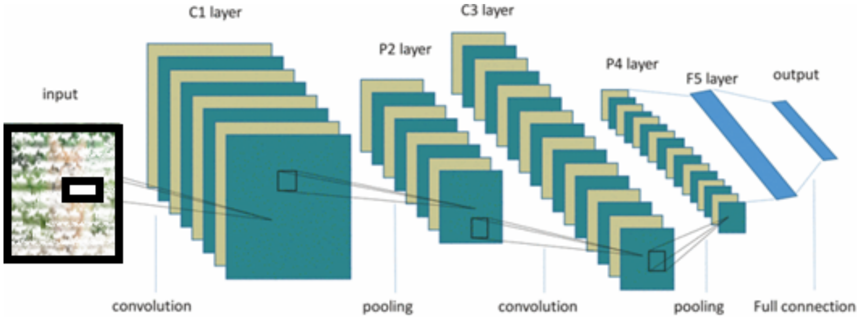
Abstract:

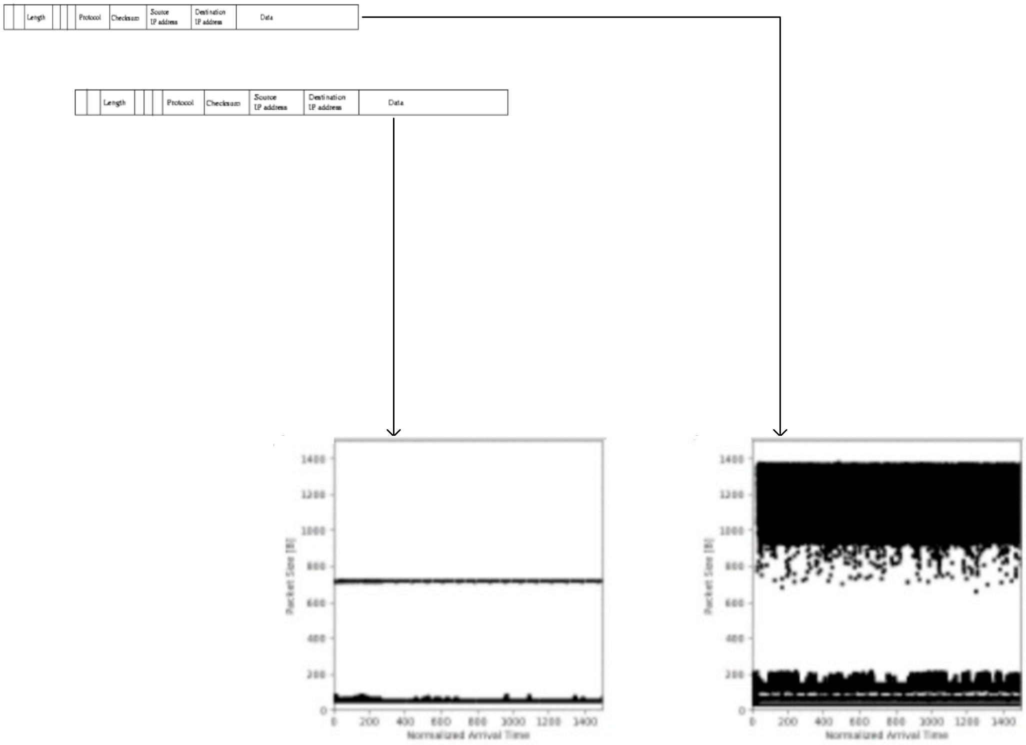
Traffic classification, the categorization of network traffic into appropriate classes, is important to many applications, such as quality of service (QoS) control, pricing, resource usage planning, malware detection, and intrusion detection. Because of its importance, many different approaches have been developed over years to accommodate the diverse and changing needs of different application scenarios. In particular, the growing trends of Internet traffic encryption and an increase Virtual Private Networks (VPNs) and The Onion Router (ToR) usage, raise additional challenges to network traffic classification.

Traffic classification techniques have evolved significantly over time. The first and easiest approach is to use port numbers. However, its accuracy has been decreasing because newer applications either use well-known port numbers to disguise their traffic or do not use standard registered port numbers. Despite its inaccuracy, the port number is still widely used either alone or in tandem with other features in practice. The next generation of traffic classifiers, relying on payload or data packet inspection (DPI), focuses on finding patterns or keywords in data packets. These methods are only applicable to unencrypted traffic and has high computational overhead. As a result, a new generation of methods, based on flow-statistics, emerged. These methods rely on statistical or time series features, which enable them to handle both encrypted and unencrypted traffic. These methods usually employ classical Machine Learning (ML) algorithms, such as random forest (RF) and k-nearest neighbor (KNN). However, their performance heavily depends on the human-engineered features, which limit their generalizability.

Deep Learning (DL) obviates the need to select features by a domain expert because it automatically selects features through training. This characteristic makes DL a highly desirable approach for traffic classification, especially when new classes constantly emerge and patterns of old classes evolve. Another important characteristic of DL is that it has a considerably higher capacity of learning in comparison to traditional ML methods, and thus can learn highly complicated patterns. Combining these two characteristics, as an end-to-end approach, DL is capable of learning the non-linear relationship between the raw input and corresponding output without the need to break the problem into the small sub-problems of feature selection and classification. To achieve this goal, DL requires sufficient labeled data and adequate computation power. In this project, we will deploy a framework for traffic classification task, including data collection and cleaning, feature selection, and model selection.

In this project we will use an innovative approach. The Internet traffic flows will be transformed into FlowPic images and from this point, we will take advantage of current advances in the field of image recognition using DL methods, and design a Convolutional Neural Network (CNN) architecture to successfully classify the traffic.





(a) Netflix (b) Skype

Goals:

- **Review related papers:**
  - The Applications of Deep Learning on Traffic Identification- https://www.blackhat.com/docs/us-15/materials/us-15-Wang-The-Applications-Of-Deep-Learning-On-Traffic-Identification-wp.pdf

    - FlowPic: Encrypted Internet Traffic Classification is as Easy as Image Recognition - https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8845315&tag=1
    - Seq2Img: A sequence-to-image based approach towards IP traffic classification using convolutional neural networks - https://ieeexplore.ieee.org/abstract/document/8258054

- **Project steps:**
    - Focus on FlowPic
    - Train the Convolutional Neural Networks (CNN) model with the FlowPics
    - Test the model with the downloaded pcap files
    - Test the model with recorded pcap files
    - Stretch goals:
        i. Add "RGB" data to the FlowPic – for example:
            1. Forward Inter Arrival Time (fiat)
            2. Backwards Inter Arrival Time (biat)

        ii. Add FlowPic for QUIC flows or VPN style flows.

        iii. Minimize the delay of the analysis. Currently it is 30 seconds.

Requirements:

Introduction to Networking (Must), Internet Networking (Optional)

Introduction to Artificial Intelligence (Must)

or

Introduction to Machine Learning (Must)

Or an equivalent ML course

Programming Language:
Python , Java Script

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