

FlowPic: Encrypted Internet Traffic Classification is as Easy as Image Recognition

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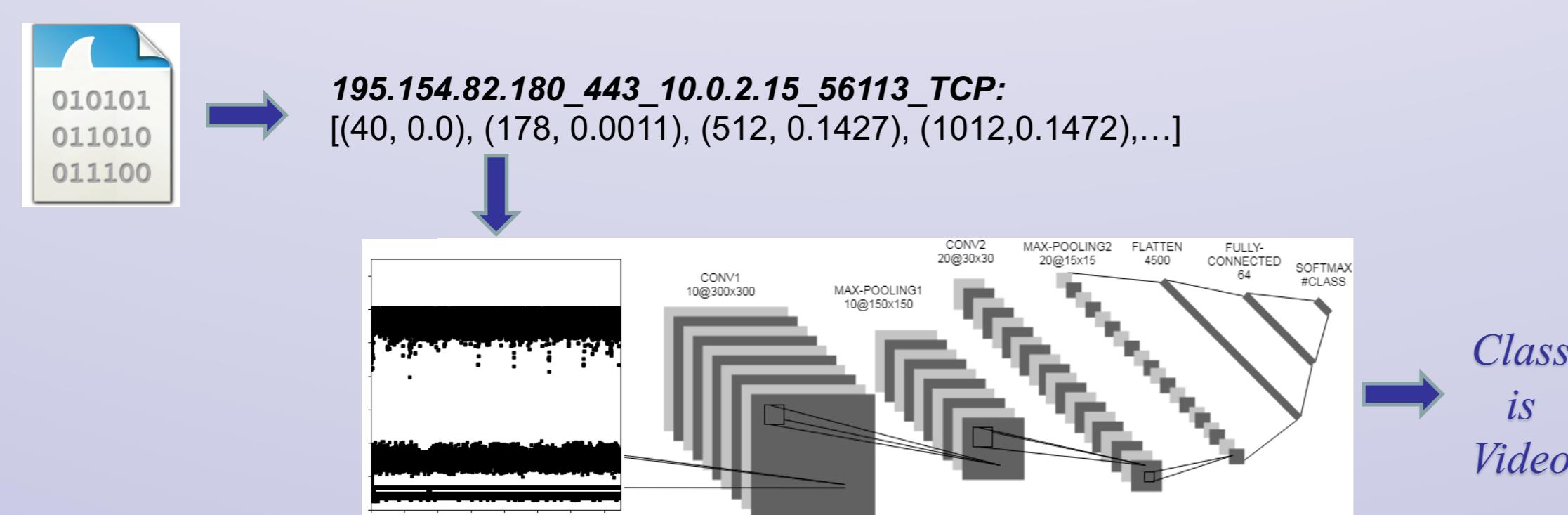
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Introduction

- Given a tap on a communication channel, our aim is to classify the flows even if they are passing through VPN or Tor.
- Our goal is to propose a **generic approach** for Internet traffic classification:
 - We use the exact same architecture for all the experiments.
 - Dealing with all kinds of Internet traffic classification problems.
- Using all time and size related information available** in a network flow, instead of just using information from manually extracted features.
- Dealing with **only a time window of a unidirectional flow** instead of the entire bidirectional session.
- Do not rely on the packet payload content:**
 - Do not breach privacy.
 - Minimalizing storage requirement.
 - Classifying VPN and Tor traffic.
- Capturing an intrinsic characteristic of a category behavior, regardless of the encryption technique and a specific user.

Approach

- Extract records from each flow, which comprised of a list of pairs, {IP packet size, time of arrival} for each packet in the flow.
- Split each unidirectional flow to equal blocks (15/60 seconds).
- Generate 2D-histogram. For simplicity, we set the 2D-histogram to be a square image.
- Feed a LeNet-5 style Convolution Neural Network.



FlowPics Exploration

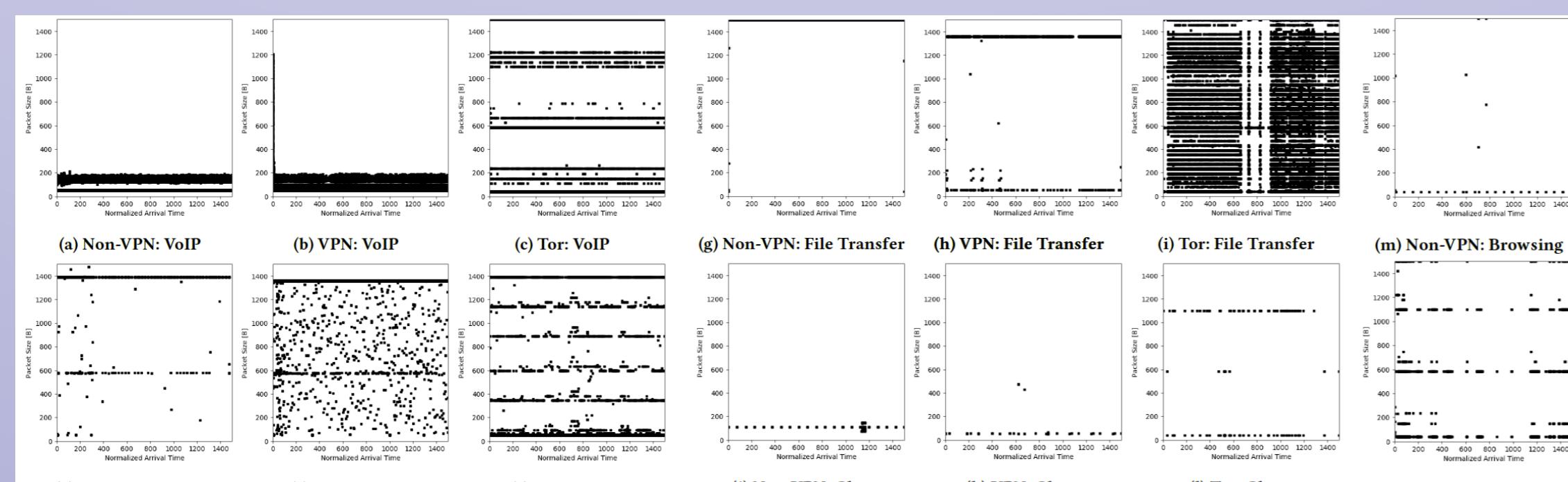


Figure 1: Examples of FlowPics for VoIP, video, file transfer, chat and browsing over non-VPN, VPN and Tor.



Figure 2: Examples of FlowPics for several video applications.

Experiments and Results

We use labeled datasets of packet capture (pcap) files from the Uni. of New Brunswick: "ISCX VPN-nonVPN traffic dataset" (ISCX-VPN)[15] and "ISCX Tor-nonTor dataset" (ISCX-Tor) [21], as well as our own small packet capture (TAU), and conduct different types of experiments; (1) multiclass classification experiments over non-VPN/VPN/Tor and merged dataset, (2) class vs. all classification experiments, (3) application identification, and (4) classification of an unknown application.

Problem	FlowPic Acc. (%)	Best Previous Result			Remark	
		Training/Test	Non-VPN	VPN	Tor	
Non-VPN Traffic Categorization	85.0	84.0 %	Pr. Gil <i>et al.</i> [22]			Different categories. [22] used unbalanced dataset
VPN Traffic Categorization	98.4	98.6 %	Acc., Wang <i>et al.</i> [7]	[7]		Classify raw packets data. Not including browsing category
Tor Traffic Categorization	67.8	84.3 %	Pr. Gil <i>et al.</i> [22]			Different categories. [22] used unbalanced dataset
Traffic Categorization over Merged Dataset	83.0					
Non-VPN Class vs. All	97.0 (Average)					
VPN Class vs. All	99.7 (Average)					
Tor Class vs. All	85.7 (Average)					
Encryption Techniques	88.4	99. %	Acc., Wang <i>et al.</i> [7]	[7]		Classify raw packets data, not including Tor category
Applications Identification	99.7	93.9 %	Acc., Yamansavascilar <i>et al.</i> [9]			Different classes

No previous results

Class	Accuracy (%)	Training/Test	Non-VPN	VPN	Tor
VoIP	99.6	Non-VPN	99.4	48.2	
	95.8	VPN	99.9	58.1	
	52.1	Tor	35.8	93.3	
Video	99.9	Non-VPN	98.8	83.8	
	54.0	VPN	99.9	57.8	
	55.3	Tor	86.1	99.9	
File Transfer	98.8	Non-VPN	79.9	60.6	
	65.1	VPN	99.9	54.5	
	63.1	Tor	35.8	53.8	
Chat	96.2	Non-VPN	78.9	70.3	
	71.7	VPN	99.2	69.4	
	85.8	Tor	93.1	89.0	
Browsing	90.6	Non-VPN	-	57.2	
	-	VPN	-	-	
	76.1	Tor	-	90.6	

Table 2: Class vs. all classification accuracy performances.

Table 1: A summary table of our results for different traffic classification problems, with comparison to best known previous results over the ISCX dataset.

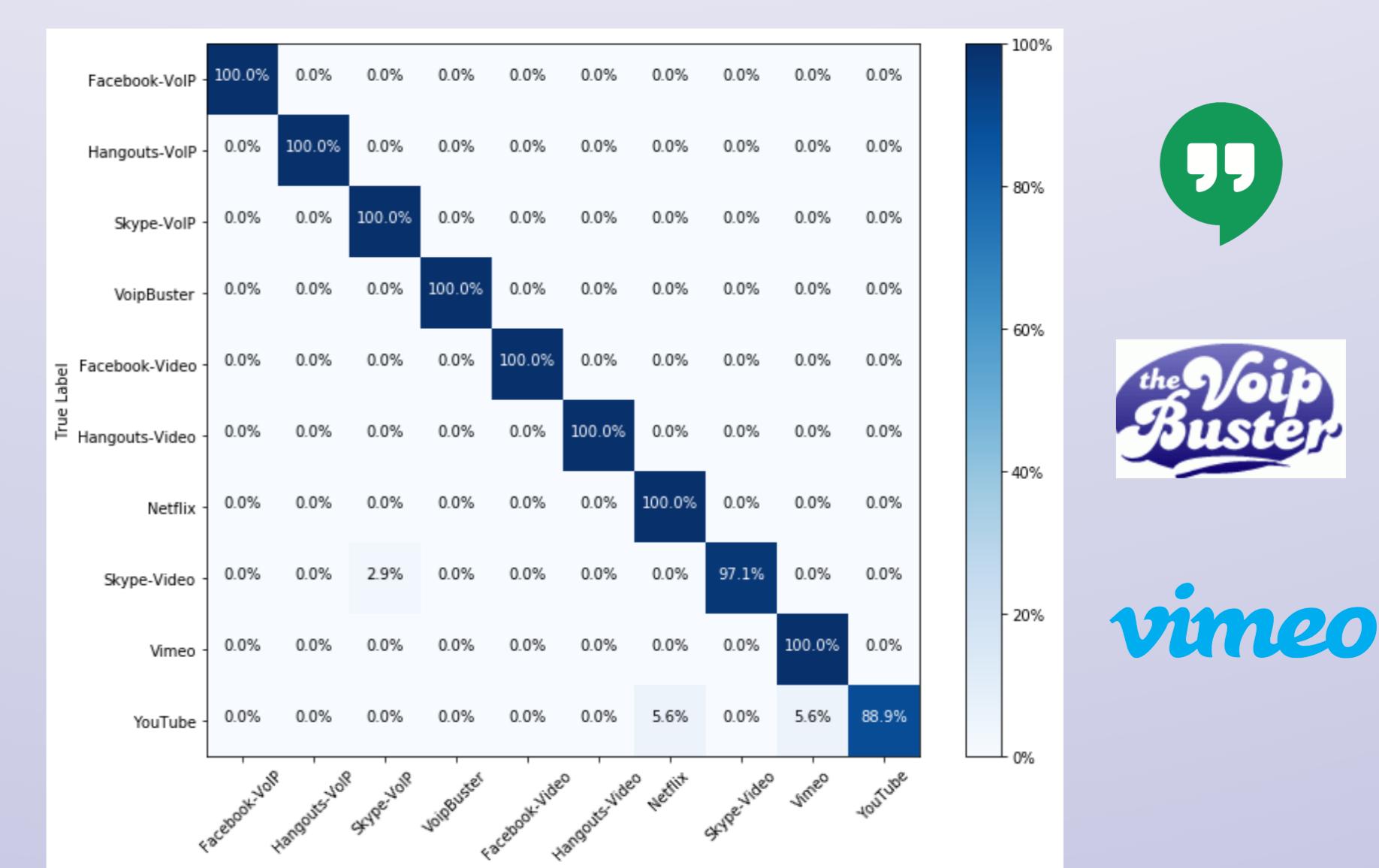


Figure 3: A confusion matrix of the VoIP and video applications identification problem.

Conclusions

- A **generic approach** for Internet traffic classification:
 - We use the exact same CNN architecture for all the experiments.
 - Dealing with all kinds of Internet traffic classification problems;** traffic categorization, application identification, encryption techniques.
- We are the first to show:
 - Identifying traffic category of an unfamiliar application**, by learning samples of other applications of the same traffic category.
 - Classifying different Internet traffic categories that pass through different encryption techniques by learning traffic that pass through other encryption techniques.
- Fast & simple:** Classification is done after the first **15 seconds of a unidirectional flow**.
- No need for manual extraction of features.**
- Good results for traffic over VPN and Tor.

References

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You can find more details in - <https://ieeexplore.ieee.org/document/8845315>