De-anonymizing Encrypted Video Streams

Master's Thesis

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Abstract

In the last recent years streaming services such as Netflix, Youtube, Amazon Prime Video, Hulu and others, have become the main source for video content delivery to the public. With the effort of private companies and of the AOM consortium [1], various coding formats and streaming techinques have been refined and have gained popularity. *Adaptive Bitrate Streaming*, between others, enables high quality streaming of media content over HTTP, and represents nowadays the industry's standard.

DASH *Dynamic Adaptive Streaming over HTTP* is an instance of Adaptive Bitrate Streaming originally developed by MPEG. In DASH each media file gets encoded at multiple bitrates, which are then partitioned into smaller segments and delivered to the user over HTTP. As of today, Netflix makes extensive use of DASH, by encoding each title in their catalogue at different quality levels, so that the user is served tailored-size content depending on network conditions, and its device capabiities [2].

DASH and *variable-bitrate-encoding*, have proven to be leaking potentially harmful data. Reed et Al. [3] have shown, how despite a recent upgrade in Netflix infrastructure to provide HTTPS encryption to video traffic, it is possible to recover unique fingerprints for each title, and to use them to match against captured traffic. In their study, they make use of adudump [4] a command-line program that can run on passive TAP devices [5] or on a live network interface, and uses TCP and ACKs sequences to infer the size of application data units *ADUs* transferred over each TCP connection in real time.

Our approach reiterates parts of Reed et Al.'s work, but cannot rely on their every assumption and discovery, due to constant changes that Netflix is integrating into their enconding and streaming algorithms. Moreover our intent is focused on finding out if, by analyzing coarse-grained traffic data, we are able to identify a video based on its *bitrate-ladder*.

TODO: *refine it and add results*

Contents

1

Introduction

According to the latest Cisco's VNI [6], video will account for 82% of all IP traffic in Europe by 2021; in addition, the overall IP traffic per person will triplicate from 13*GB* to 35*GB*. These forecasts clearly picture the growth of the streaming industry, posing, at the same time an important question on the present and future states of the final user's privacy.

As shown by Reed et Al. [3] anonimity of user's viewing activity is at risk. Not for the use that Netflix or other streaming services do of user's session data, but because of the risk of a man-in-the-middle attack *MITM* carried by an *evil* party that has control over the flow of packets over a network.

In particular, they have shown how the adoption of HTTPS to protect video streams from Netflix *CDN*s to user's end devices, does not hold against passive traffic analysis.

1.1 Motivation

The goal of this project is to replicate part of the work conducted by Reed et Al. and to investigate the possibility of identifying a Netflix stream solely based on the observed average bandwidth. This, follows from the intuition that *per-title encoding* embeds the nature and the complexity of video frames in a unique way, that may reveal the identity of the content being streamed.

1.1.1 Per-Title Encoding

In December 2015 Netflix announced [2] that it was introducing a new method to analyze the complexity of each title and find the best encoding recipe based on it. Their goal with the adoption of per-title encoding was to provide users with better quality streams at a lower bandwidth.

Before then, each title was encoded with a *Fixed Bitrate Ladder*; their pipeline returned a list of {*Bitrate, Resolution*} pairs that represented the sufficient bitrate to encode the stream at a certain resolution (Table 1.1), with no visible artificats.

Bitrate (kbps)	**Resolution**
235	320×240
375	384×288
560	512×384
750	512×384
1050	640×480
1750	720×480
2350	1280×720
3000	1280×720
4300	1920×1080
5800	1920×1080

Table 1.1: Netflix original's Fixed Bitrate Ladder.

This "one-size-fits-all" ladder, as reported, achieved good results in the encoded video's perceived quality (**PSNR** [7]) given the bitrate constraint, but, would not perform optimally under certain conditions. For instance, high detailed scenes with sudden changes of light, or rapid transitions of camera shots, would require more than 5800*kbps*; in contrast, more static frames, as in animated cartoons, may be encoded at higher resolutions mantaining the same bitrate level.

In summary they noticed how in certain cases, the produced encoding would either present some small artifacts (*e.g.* complex scenes), or waste bandwidth, (*e.g.* static, plain scenes). For this reason, they came up with per-title encoding.

In order to find the best fitting bitrate ladder for a particular title, there are several criterias that they took into account, the principal ones being:

- How many quality levels should be encoded to obtain a *JND* between each of them.
- Best {*Resolution, Bitrate*} pair for each quality level
- Highest bitrate required to achieve the best perceivable quality

As aforementioned, each title's perceived video quality, gets computed as a measure of *Peak signal-to-noise ratio*. The comparison is performed between the produced encode, upsampled to 1080*p*, and the original title in 1080*p*, and the best {*Bitrate, Resolution*} pair is assigned to that specific quality level, as depicted in Table 1.2.

In Figure 1.1, we can see the impact of per-title encoding on the original bitrate ladder: in order to achieve the same perceivable quality level (point **B** and **C**), it requires a lower bitrate to be encoded to (point **A**). Moreover, with around the same bitrate, one can see

Resolutions	Fixed Bitrate Ladder (kpbs)	Per-Title Bitrate Ladder (kbps)
320×240	235	150
384×288	375	200
512×384	560	290
512×384	750	
640×480	1050	
720×480	1750	440
720×480		590
1280×720	2350	830
1920×1080	3000	1150
1920×1080	4300	1470
1920×1080	5800	2150
1920×1080		3840

Table 1.2: Comparison between the two different approaches for the same title: note how different titles may have different numbers of quality levels. For each movie, the minimum number of quality levels gets computed to produce a just-noticeable-difference (JND), when switching bitrates during playback.

how per-title encoding can achieve a higher resolution compared the fixed case (point **A** and **D** respectively). It follows obviously that, holding to a high-quality stream while maintainig or lowering the used bandwidth is key: the end user will get same or better quality then before, at a lower bandwidth.

1.1.2 User's Privacy

As of 2018, data began the most valuable commodity on the planet [8], and with its value rising, society starts to question how to legislate to protect both industry's and user's rights.

In 2016, Netflix announced the introduction of HTTPS to protect the content being streamed to users. With the addition of TLS on top of HTTP, Netflix aim, was to avoid the risk of eavesdropping on unsecure connections, protecting themselves and users from third-party applications and governments potentially collecting viewer's data and streaming habits.

Avoiding deep packet inspection from potential eavesdropper certainly adds another layer of security, but given the narrow relationship between Netflix and ISPs, one might conclude that the chance that IP packets do not get inspected by ISPs (especially in the United States, after the reclassification of ISPs as Title I *Information Services* [9]), is still a matter of mere trust given to the platform-provider relationship.

Cases of user's data breaches as the Kanopy one [10], are a testimony of how easy would be for an attacker to extract information to the point at which users could become

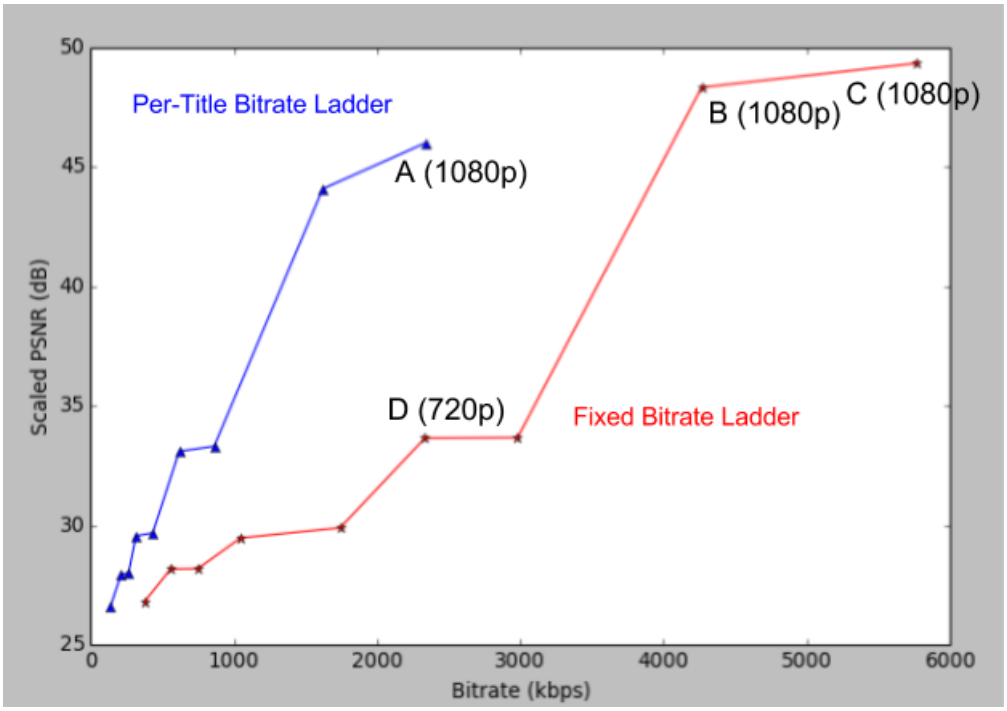

Figure 1.1: Difference between per-title vs. fixed bitrate ladders.

identifiable by the solely information the platform was collecting in their internal log files. The content of which, include between others: timestamps, geo-location data, client-device informations and IP addresses.

The ability to cluster people based on just their video-streaming habits, poses a potential threat for how the data could be processed and used by parties with access to it. One could imagine how government agencies could easily get in possess of sensitive information about the nature of the content a particular user is interested about, or how ISPs could profit from selling data profiles to advertisement companies that in turn would exploit their information to improve per-user recommendation algorithms.

Considering this trend, it is for us crucial to investigate how parties that can have access to transport-layer information, (more details in Chapter 3), could exploit per-title encoding to identify video traffic.

1.2 Related Work

As previously mentioned, our work is mainly insipired by Reed et Al.'s [3] research paper, in which they presented a novel method to de-anonymize encrypted netflix stream in real-time with limited hardware requirements. Their system was able to identify a video using uniquely TCP/IP headers, by making use of `adudump`, a program built on

top of *libpcap* [11], a powerful C library for network traffic capture. They acquired for each video, metadata information with a tampering tool, and then matched adudump traces against with. The evaluation of their method revelaed that they could identify majority of videos by recording only 20 minutes of traffic each.

An earlier proof on how bandwidth analysis could reveal the content of ecnrypted traffic, was given by Saponas et Al. [12], in their "SlingBox-Pro" case study, that exposed how, by recording network traffic and producing and combining different trace levels, they were able to identify 98% of 40 minutes video traces.

Similar work has been conducted also by Moser [13], who analyzed how bitrate ladders could uniquely embed the identity of Netflix titles. In his work he further studies the impact of the aggregation of each video's segment bandwidth on the overall accuracy of his system.

1.3 Main Objective

The main goal of this project is to build a system that can manipulate network bandwidth and observe video traffic from Netflix, to verify the intuition that each title could be identified by its own bitrate ladder.

Furthermore we investigate and discuss possible countermeasures that streaming providers could adopt to preserve users privacy. A detailed explanation of our approach is presented in Chapter 3

1.4 Structure of this Report

In this section, we outline of the contents and the structure of this report.

Chapter 1 introduced our motivation behind the project, presented featured work that influenced and inspire our approach, and it outlined the goals we would like to ultimately achieve.

Chapter 2 presents the attack scenario from an ISP perspective, (the ISP acting as the adversary), the infrastructure needed to acquire the data, the nature of the information that could be infered, and the consequences that might arise.

Chapter 3 shows our version of the attack, in a different context, but up to some extent, with similar conditions to the one depicted in Chapter 2. It also higlights the similiarities and differences from the featured approaches we followed.

In Chapter 4 we evaluate our system, we present results, and discuss the relevance of such a method.

Chapter 5 tries to summarize and draw conclusion based on the claims made at the beginning of the project.

2

ISPs as adversaries

Of great importance to our approach, is aquiring real-time network traffic, with downstream throughput being our only focus; here discuss the potential scenarios that allow adversaries to obtain such information, and describe how, in particular ISPs, could make use of it, to identify video streaming and profile users based on their streaming habits.

2.1 Attack Scenarios

Given the nature of modern Internet infrastructure, an adversary interested in eavesdropping a particular communication, only needs to compromise a node on the path the communication travels through. An *on-path* attacker could easily gain passive access to network and transport layers, and start capturing network traffic. This can include malicious or compromised Wi-Fi access points, routers, tapped network cables and ISPs.

Rather than just attacking physical devices, leaks of information could occur in network connections, in which an attacker physically close to the victim, could make use of a *Wi-Fi sniffer* to estimate traffic by capturing physical layer WLAN packets. Information may be encrypted by 802.11, and the sniffer may not take into account packet retransmissions at the session layer nor multiple TCP/IP flows on the same link, potentially causing noise on the observation. Despite so, Reed et Al. [14], have shown that it is still possible to estimate WAP-to-client throughput and use it to identify the content being streamed.

In addition to the above, *side-channel eavesdropping* can exploit information about the network structure, to saturate a link between the user and the server, and estimate fluctuations of congestion by sending probes remotely and observing queueing delays in routers, as in [15].

We will now present the relevant phases and tools needed for an ISP to perform such attack.

2.2 Video Fingerprinting

Assuming that the ISP has no direct access to the CDN, title are stored in, it needs to build a database of video traffic to match against future video stream captures. To build such a database, the ISP needs to have access to a network interface, control its inbound bandwidth, (to get different levels of quality for each title), and capture incoming traffic passing through it.

In order to control the incoming bandwidth, the ISP could either limit it directly onto a generic L4 switch (probably more stable), or decide to connect any UNIX-like machine and throttle the throughput of its main ethernet interface. We will consider the scenario in which the ISP limits the bandwidth of the ethernet interface of the switch.

The value of the enforced bandwidth determines the quality (bitrate) of the content that will be captured. This require the ISP to choose a policy on how to throttle the bandwidth to get all different quality levels for each title. We assume the bandwidth levels to be the one shown in Table 2.1. These values, in our own version of the attack, have proven to reconstruct quite-faithfully the bitrate ladders of each title, thus we assume the ISP to use them as reference, although in reality, our approach would work with any set capable of spanning the space of bitrate levels.

Bandwidth levels (Mbps)												
0.6	0.8	1.2	2	3.5	4.2	4.8	5.5	6.5	7.05	10	15	20

Table 2.1: Enforced bandwidth levels.

TODO: *Explain briefly how the ISP needs to capture traffic to build the database*

2.3 Capturing video traffic

This, requires the ISP to be in possess of a generic L4 switch that can mirror traffic from a port to another one. Then any UNIX-like system that implements *libpcap* is suitable for capturing inbound traffic on the mirrored port, as presented below in Figure 2.1.

The UNIX machine can now listen onto the interface to which traffic is mirrored by invoking `tcpdump`.

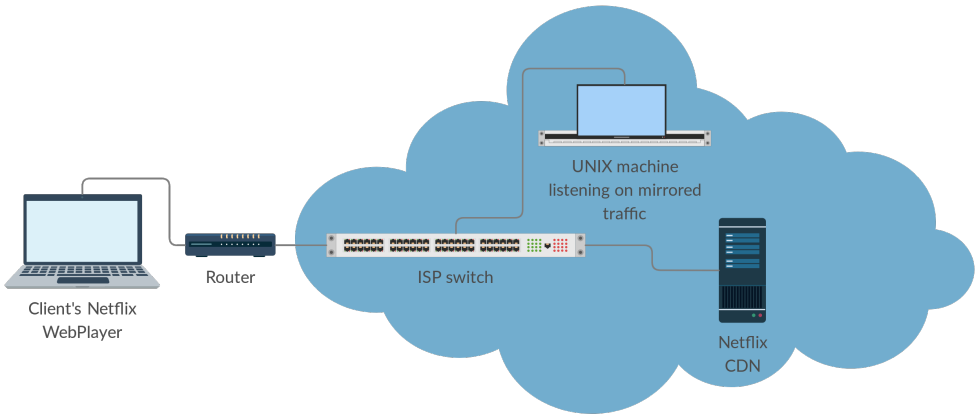

Figure 2.1: Traffic capture scenario

3

Approach

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