2015-09-30

NetFlix and Twitch Traffic Characterization

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by

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A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE

DEGREE OF MASTER OF SCIENCE

GRADUATE PROGRAM IN COMPUTER SCIENCE

CALGARY, ALBERTA

SEPTEMBER, 2015

Abstract

Streaming video content is the largest contributor to inbound network traffic at the University of Calgary. Over five months, from December 2014 – April 2015, over 2.7 petabytes of traffic on 49 billion connections was observed.

This thesis presents traffic characterizations for two large video streaming services, namely NetFlix and Twitch. These two services contribute a significant portion of inbound bytes. NetFlix provides TV series and movies on demand. Twitch offers live streaming of video game play. These services share many characteristics, including asymmetric connections, content delivery mechanisms, and content popularity patterns.

This thesis sheds light on the usage of modern video streaming services on an edge network. It's one of only a few studies to utilize long-term network-level data. To the best of our knowledge, it's one of the first studies that uses network-level data for Twitch traffic characterization, and content characterization for NetFlix and Twitch.

Acknowledgements

First, I want to thank my advisors Carey Williamson and Martin Arlitt for their assistance during the writing of the thesis. Their guidance and feedback improved my research and writing abilities.

Second, I would like to thank Darcy Grant for taking time out of his very busy schedule to answer my questions and help me configure the machines used for the thesis.

Finally, I want to thank my parents. Their contributions to my education throughout my life made this possible.

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List of Abbreviations and Acronyms

Symbol	Definition
API	Application Programming Interface
CDF	Cumulative Distribution Function
CDN	Content Distribution Network
CIDR	Classless Inter-Domain Routing
CS:GO	Counter Strike: Global Offensive
DASH	Dynamic Adaptive Streaming over HTTP
DNS	Domain Name Service
DRM	Digital Rights Management
eSports	Electronic Sports
ESL	Electronic Sports League
FPS	First Person Shooter
HD	High Definition
HLS	HTTP Live Stream
HTML	Hypertext Markup Language
HTTP	Hypertext Transfer Protocol
HTTPS	Hypertext Transfer Protocol Secure
IEM	Intel Extreme Masters
IMDB	Internet Movie Database
IP	Internet Protocol
IRC	Internet Relay Chat
ISP	Internet Service Provider
LAN	Local Area Network
LoL	League of Legends

MIME	Multipurpose Internet Mail Extension
MOBA	Multi-player Online Battle Arena
NAT	Network Address Translation
NTP	Network Time Protocol
OBS	Open Broadcaster Software
OS	Operating System
RTS	Real-Time Strategy
SC2	Starcraft 2
SSH	Secure Shell
SSL	Secure Socket Layer
TCP	Transmission Control Protocol
TLS	Transport-Layer Security
TV	Television
UDP	User Datagram Protocol
URI	Uniform Resourse Identifier
URL	Uniform Resourse Locator
U of C	University of Calgary
VOD	Video on Demand
WAN	Wide Area Network

Chapter 1

Introduction

Usage of the World Wide Web has changed greatly since its introduction to the public. From serving static documents and running servers from your home to dynamic content, content distribution networks (CDN), and uploading information to the cloud, patterns have grown more varied and asymmetrical; end users typically download far more data than they upload. Video streaming content from the Web highlights the effects of these changes. As more users are viewing streaming video content online, the volume of this type of traffic is expected to grow. Characterizing this type of traffic allows us to gain a deeper understanding of how network resources are utilized and how users are choosing to consume the content.

1.1 Motivation

Network traffic measurement is a mature area of research that is well understood. It's used in academia and in industry, for research and operational purposes. Measurement allows us to gain a general understanding of how resources are being utilized, i.e., what's the throughput for a link? It may also allow us to improve the way we are utilizing the network, via better policies, resource placement, or resource allocation. In order to plan for future improvements, it is important to continuously characterize the traffic, to adapt the network infrastructure to the evolving uses of the network.

Workload characterization in the context of a computer network explains network usage by describing the traffic on the network. Different types of workloads have different properties. For example, with Web traffic, the amount of data downloaded from the Internet is much larger than the amount of data uploaded to the Internet. Properties of traffic may be determined by meta-data provided in the traffic, or by observing the traffic itself.

Large changes in Web usage patterns are occurring as the workloads evolve. Instead of static images and text documents, users now are interested in viewing a diversity of media types online. Previously, when a user wished to view different media content they would have to acquire the file somehow. This was generally done via direct download or through some peer-to-peer application. Currently, the most popular way to consume different media is to stream it from the Web. In fact, media streaming, specifically for video, is the largest category (by byte volume) of incoming content from the Internet at the University of Calgary, as we will detail in Chapter 3.

The popularity of streaming media content has risen greatly; end users are now much more interested in streaming content than downloading it as a result of the service model. Online streaming media has grown in both the number of providers and the amount of content available. Furthermore, the growth is expected to continue [14]. It seems that music and video streaming will continue to be dominant contributers to network traffic in the future.

Music or audio content streaming services were the first to demonstrate that media streaming is viable. Popular music streaming sites today include Spotify, Rdio, and Google Play Music. Spotify and Rdio both offer free services, while Google Play provides a subscription-based music service as well as an on-demand store catalogue. These music streaming sites all offer professionally produced content and are expected to grow in popularity [9, 20].

Video streaming sites have experienced tremendous growth within the past few years. Many streaming video sites have a mix of user-generated, professionally-produced, and live-streamed content. Popular video streaming sites include YouTube [83], NetFlix [49], Twitch [75], Vimeo [79], DailyMotion [17], Hulu [31], and Yahoo Screen [82]. Online video streaming is currently displacing the more traditional TV-Broadcast system [30]. For example, the larger multi-channel networks of YouTube "are already delivering enough minutes to US audiences to challenge major TV networks..." [30]. NetFlix and Twitch both also serve

enough content to viewers that they compete with some of the larger networks. NetFlix already serves more traffic than two of the four major US television networks, while Twitch serves enough content to rank in the top 75 networks, and is expected to rank in the top 25 networks next year based on its projected growth [30].

1.1.1 Video Content Providers

One of the most popular video content providers is NetFlix [35]. For this study we collected information about (unencrypted) NetFlix traffic from December 2014 to the end of April 2015. NetFlix plans to encrypt all of their service later in 2015, starting with the Web interface [50]. NetFlix charges a monthly subscription fee for unlimited access to its content. Since NetFlix deals with licensing issues around the world, they sometimes impose a geographical restriction on its content; i.e., when accessing NetFlix in the United States, a lot more content is available than if accessing from Canada. The selection of content in Canada has improved greatly over recent years, but people still use various methods to bypass the regional restrictions. We will discuss the methods to bypass such restrictions further in Chapter 2.

Twitch is a video content site that primarily focuses on the live-streaming of video games being played by other people. Twitch provides video-on-demand archives of streams for later viewing. The content that Twitch serves is related to video games or non-sports games of some sort. The games may be played and viewed at a professional level, with teams of professional gamers facing off against each other and casters[1] commentating about the game as it happens, or it can be someone trying a game for the first time and explaining what they are trying in the game and what they think of it. Twitch is the leading Web site for eSports[2] broadcasting [59]. All gaming tournaments have a stream on Twitch for their

[1] A caster is a professional commentator for these events.

[2] eSports is the shorthand term for electronic sports, which are competitive multi-player video game competitions. In this thesis, the term eSports generally refers to such games being played at a professional level.

matches. There are some other Web sites that provide live-streaming for eSports events or for games generally, but they do not have nearly as much traffic as Twitch does, or in the case of covering an eSports event, they provide a stream on Twitch as well. Twitch accounts for a significant portion of Internet traffic in the United States, trailing sites like YouTube, NetFlix, and Apple, but ahead of others such as Facebook and Hulu [22].

We did not characterize the traffic from other providers as deeply as we did for NetFlix and Twitch. YouTube is the largest video sharing site in the world [3], and generates the largest volume of video traffic on the University of Calgary's network. Since December 2012, however, they have essentially encrypted all of their traffic. The traffic generated from other video sharing sites is low in volume and is less interesting than Twitch (since Twitch is mostly live-streamed). Sites such as Vimeo and DailyMotion both offer similar services to YouTube, however they have a smaller and less active user community, and do not generate as much traffic. Vimeo and DailyMotion transport their content over unencrypted connections and may be assisted by a third party, i.e., a content distribution network. Hulu and Yahoo Screen both offer professionally-made content (such as TV shows), but are either not officially provided in Canada, as is the case with Hulu, or have almost no content in Canada, as is the case with Yahoo Screen. Hulu delivers its content over unencrypted connections, and may be assisted by a third party. Yahoo Screen uses encrypted connections, and seems to serve content from its own servers. Vimeo may provide all content in high definition (HD), uses encrypted connections on its site, and uses services from third parties to deliver content. DailyMotion uses unencrypted connections and serves content from its own servers. All of these sites account for very little traffic overall at the University of Calgary.

1.2 Objectives

The objectives of this thesis are as follows:

- Develop a methodology to measure all campus traffic for an extended period

of time.

- Characterize the current usage trends for the University of Calgary's network.
- Understand and characterize popular video streaming services accessed from the University of Calgary's network.
- Identify approaches to improve the delivery of popular streaming services.

In order to accomplish the latter two objectives, we need to accomplish the initial two objectives.

1.3 Contributions

The four main contributions of this thesis are as follows. First, we construct the measurement infrastructure needed to monitor all campus traffic for an extended period of time. Second, we use the collected data to better understand network utilization at the University of Calgary. Third, we focus on characterizing two popular unencrypted video services used on campus, namely NetFlix and Twitch. Finally, we identify several approaches to improve the delivery of popular streaming services.

Measuring all campus traffic identified a few issues that we describe in Chapter 3. When characterizing the University of Calgary's network utilization, we observed many phenomena, including some recent changes to Web usage. While measuring traffic for an extended period of time, we observed instances of abnormal behaviour on the network. A change that has occurred in recent years with regards to Web usage is the increased usage of encrypted (HTTPS) connections. The usage of encrypted connections greatly limits our ability to perform a detailed characterization of Web traffic. We focus on characterizing NetFlix and Twitch traffic since they are relatively new services that are popular (both locally and globally), and are expected to grow. Measuring the two providers is interesting since they do not have overlap in content; NetFlix provides a catalogue of on-demand content for the user

to view, and Twitch focuses on live-streamed content. Furthermore, both of these services were unencrypted during our collection period.

1.4 Organization

This thesis is organized as follows. Chapter 2 provides a brief overview of the Internet's TCP/IP architecture, approaches to streaming media, and an introduction to NetFlix and Twitch. It also covers previous work done in network traffic measurement and video traffic characterization. Chapter 3 describes the tools and methodology used to collect the data and discusses some information about general traffic levels at the University of Calgary. Chapter 4 explains general information about the levels of video traffic that we have observed at the University of Calgary. Chapter 5 contains an analysis and characterization of NetFlix, and Chapter 6 provides the same for Twitch. Finally, Chapter 7 presents conclusions and future work.

Chapter 2

Background and Related Work

This chapter provides an overview of the protocols involved in computer networking, as well as approaches to media streaming, network measurement, and video traffic analysis. Section 2.1 describes the TCP/IP stack used to transfer data over the Internet. Approaches to media streaming are summarized in Section 2.2. Other studies in network and Web traffic measurement are introduced in Section 2.3, and related work on video traffic characterization is discussed in Section 2.4. Background information on NetFlix and Twitch is covered in Sections 2.5 and 2.6, respectively.

2.1 TCP/IP Architecture

The Internet's structure and usefulness have arisen from the organization of its protocols. These protocols are layered, and are referred to as the Internet protocol suite or TCP/IP (after two of the most important protocols in the suite). We will describe the standard five-layer model of the TCP/IP stack. As shown in Figure 2.1, the layers are physical, data link, network (or Internet), transport, and application [37]. Some of our later work on application-level traffic classification relies on assumptions drawn from the TCP/IP stack.

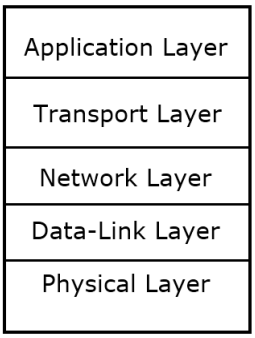


Figure 2.1: The TCP/IP Layered Protocol Stack

When two devices wish to communicate across the Internet, they do so with the assistance of intermediate nodes called routers or switches. These nodes may not necessarily implement all layers of the TCP/IP stack to assist the endpoints. Layers from the TCP/IP stack may be implemented with either hardware or software.

2.1.1 Physical and Link Layers

The lowest two layers of the stack, data link and physical, deal with preparing the data packets for transmission in frames, and transmitting the bits across a physical medium, respectively. These two layers are normally implemented in the hardware on all nodes across the network, from clients and servers on the ends to routers and switches in the middle. The physical layer moves individual bits across a physical medium (such as copper, fibre-optic lines, or wireless transmission). The link layer moves frames from one component of the network to another. Some of the most commonly used data-link layer protocols are Ethernet and Wi-Fi. Messages sent from the upper layers may be transported with a variety of different data-link and physical protocols [37]. Our work in this thesis does not utilize information from these lower layers.

2.1.2 Network Layer

The network layer sends individual data units (referred to as datagrams or packets) between the end hosts involved in a connection. Currently, the main protocol used in this layer is the Internet Protocol version 4 (IPv4) [61]. Each end host using the Internet Protocol has an address called an IP address. An IPv4 address is a four-byte value written as $a.b.c.d$, where each octet (byte) is a number from 0 to 255. The responsibilities of the network layer are to route and forward packets. Routing packets means that the router will choose the 'best' path to send the packet so that it reaches its destination [37]. Forwarding packets means that the receiving device moves packets from the input to the output port of a router. Switches in the middle of a network do not implement the network layer, but routers do.

The Internet Protocol is a "best effort" protocol. This means that it does not guarantee delivery of packets within time constraints (or delivery at all), or that the packets it sends arrive in the same order that they were sent [61]. The "best effort" nature of the Internet greatly influences application-level protocols, as we will see later in Section 2.4.

To more easily manage the IP addresses in various networks, Classless Inter-Domain Routing (CIDR) [24] is used. With CIDR, an organization is given a 'block' of addresses, referred to as a subnet. Blocks use the following notation in an IPv4 network: $a.b.c.d/x$, where the first x bits are a common prefix across all addresses in the subnet. We use subnets in this thesis when identifying traffic from NetFlix.

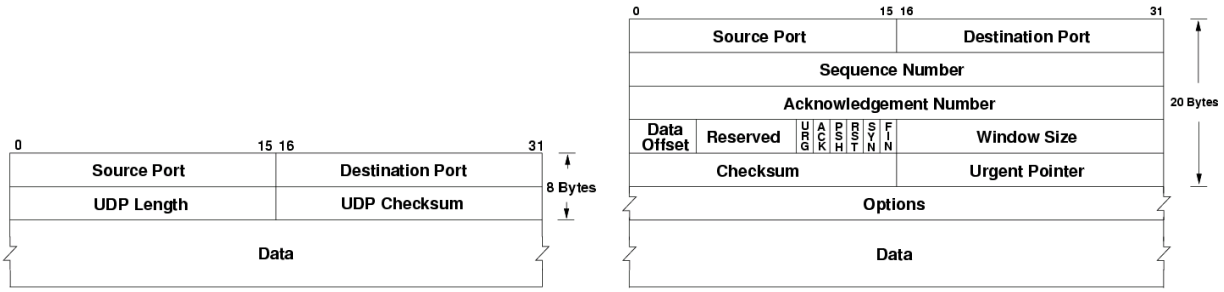
2.1.3 Transport Layer

The transport layer sits on top of the network layer, and is responsible for providing transparent end-to-end communications between processes on the individual end devices. Different transport-layer protocols may provide additional services, such as ordered delivery. The two most-used protocols at the transport layer are UDP [60] and TCP [62]. In the following subsections, we will examine the UDP and TCP protocols, as well as explain the functionality and purpose of port numbers.

UDP

The User Datagram Protocol (UDP) [60] is a connection-less protocol used to provide "best effort" delivery. When using UDP to communicate, messages may arrive out-of-order, and there is no effort made to ensure a message that has been sent is received. UDP also does not have any sort of flow or congestion control mechanism. When compared to TCP, UDP does not provide much. An illustration of the UDP header is visible in Figure 2.2a.

The applications that use UDP are those that are able to tolerate loss. Streaming media applications benefit from the use of UDP since they are tolerant of loss and prefer the low overhead of UDP. However, modern streaming media is typically done over HTTP via a



(a) UDP Header Fields

(b) TCP Header Fields

Figure 2.2: Packet Headers

TCP connection. TCP-based connections are used since many firewalls block UDP traffic, and video streaming protocols over HTTP are more robust, as discussed in Section 2.4. Furthermore, usage of UDP may negatively impact TCP flows that traverse the same links.

TCP

The most commonly used transport protocol on the Internet is the Transmission Control Protocol (TCP) [62]. TCP is a connection-oriented protocol. TCP connections provide a lot of features when compared to UDP flows. TCP provides reliable delivery; packets that are sent through TCP are delivered in order, but no guarantee is made on the amount of time it takes to deliver a packet. Many services that use TCP cannot tolerate loss. Examples include email, file transfer, and Web browsing (video streaming potentially can tolerate loss, but still uses TCP).

All packets sent through TCP have some overhead associated with them in the form of the TCP header. The TCP header is longer than a UDP header since it contains information about the packet being sent as well as information about the connection itself. Header information includes fields such as the sequence number of the packet, the acknowledgement number, window size, as well as other options and various flags. See Figure 2.2b for an illustration of a TCP header. The sequence and acknowledgement numbers in the packet header are used to ensure that data is sent and delivered in the correct order. The window size is used to indicate the receive window size for flow control; flow control in TCP ensures

that the sender will not overwhelm the receiver with data. The congestion control mechanism of TCP may limit the sending rate to ensure that the network itself is capable of handling the communication. The flags in the header are used for congestion control as well as connection control information (establishment and termination).

In order to establish a connection, the originator first sends a packet that has the SYN flag of the header set. Upon receiving the packet, the destination responds with a packet that has the SYN and ACK flags of the header set, if it is indeed willing to establish a connection. After the originator receives this packet, it will send a second packet that has the ACK flag of the header set, and it may then start transmitting data. See Figure 2.3 for an illustration of the TCP SYN handshake packet exchange sequence. Established TCP connections are typically terminated with another handshake similar to the one used for connection establishment, except with the FIN flag set (instead of SYN).

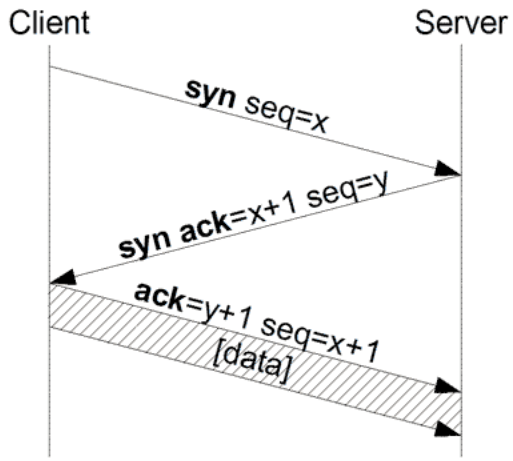


Figure 2.3: TCP Connection Establishment Handshake Procedure

When data is transmitted in the connection, the sequence and acknowledgement numbers are used to keep track of sent data. Each transmitted packet is assigned a cumulative sequence number indicating the byte(s) contained in the packet. If the sequence number overflows it wraps back to zero. When a packet is received, the receiver responds with a packet of its own that has the ACK flag set and the acknowledgement number set to indicate

the bytes received. This ACK packet tells the sender that the destination has received that packet. If no ACK packet is received in time, the sender will assume that the packet has been lost and try to retransmit it. When a group of three ACK packets for the same sequence number is received, that indicates that the destination is informing the sender that a packet has been lost and needs retransmission.

Port Numbers

Table 2.1: Well Known Port Numbers

Transport Protocol	Port Number	Service
TCP	22	SSH
TCP	80	HTTP
TCP	443	HTTPS
UDP	53	DNS
UDP	123	NTP

Port numbers are used by the transport layer to enable concurrent communication between multiple different processes on the end devices. When a process on a server starts, it may bind itself to a port and listen for incoming connections. A client process will also open a port on its machine and send data to the server; the client and server port numbers do not have to be the same. Port numbers are 16-bit numbers ranging from 0 to 65,535. Numbers less than 1,024 are considered to be reserved for a specific service or application. In many cases, a port number and the transport protocol may be used to indicate well-known services. Table 2.1 contains a few examples. For instance, a server listening to TCP port 22 is usually running secure shell (SSH). The port numbers and services that are of interest to us for this thesis are TCP ports 80 and 443, which handle HTTP and HTTPS, respectively. Port numbers in the 1,024-65,535 range are ephemeral. That is, they are used if the client does not require the port to be a specific number. For example, if a client opens a Web browser and connects to a Web site (using HTTP), the client's Web browser will have TCP connections with ports in the ephemeral range, and the server will listen on TCP port 80.

2.1.4 Application Layer

The Application layer is the uppermost layer of the protocol stack. Popular applications include email, file transfer, voice over IP (VOIP), and Web browsing. The protocols used in the TCP/IP stack should be transparent to the application. Encryption of communications can be done at the application level, for example with the TLS [18] or SSL [23] protocols.

The World Wide Web was primarily created by Tim Berners-Lee in 1989 [6]. The Web provides a platform to access content and services. Usage of the Web is how most people interact with the Internet. This is primarily done over HTTP or HTTPS.

Hypertext Transfer Protocol

The HyperText Transfer Protocol, HTTP, is one of the protocols used when browsing the World Wide Web [21]. HTTP specifies how a client requests documents from a server. The client's implementation of the protocol is typically done in a Web browser (such as Google Chrome, Mozilla Firefox, or Microsoft's Internet Explorer) to provide a user-friendly interface. As Section 2.1.2 stated, devices on the Internet are assigned an IP address; IP addresses are not intended to be human-friendly. To give users a better experience when browsing the Web, we instead address machines with a host (or domain) name; these names are translated to IP addresses by a service called the Domain Name Service (DNS) [47].

In order to differentiate between distinct objects on the Web, we use a Uniform Resource Locator (URL) or a Uniform Resource Identifier (URI). The terms URI and URL may be used interchangeably [77]. The difference between them is that a URI needs to uniquely identify a resource [7], while a URL identifies the resource as well as an access mechanism [8]. A URL is composed of two parts. The first part is the host name – which server to contact. The second part is the request path – where the item is located on the server. For example, a URL may look like "`http://google.com/`". In this case, the HTTP protocol is being used ('`http://`'), the host name is '`google.com`', and we are requesting the 'root' item ('`/`').

An HTTP request starts with a request line, which is the request method followed by

the URI, followed by the HTTP version. On the subsequent lines of the request, there may be optional headers and then an optional body. An HTTP request may look like:

```
GET /index.html HTTP/1.1
Host: www.server.com
User-Agent: my-browser/1.0
```

In this example, 'GET' is the request method being used; 'index.html' is the file being retrieved, and HTTP/1.1 is the version of the Hypertext Transfer Protocol being used for the request. The response may indicate a different HTTP version that the server has decided to use for the connection. The headers in our example include the Host as well as the User-Agent used to request the element, and there is no body for this request. The most popular request methods are GET, POST, and HEAD. GET requests are used to retrieve an item from a server. POST requests are used to send information to a server (in the request body). HEAD requests are used to retrieve just the meta-data about an object from the server (no body in the response).

When a Web server receives an HTTP request, it will issue a response. Responses start with a status line, then a set of optional headers, followed by the (optional) body. The status line starts with the HTTP version, followed by the response status code, then the response reason-phrase. An example of a response may look like:

```
HTTP/1.1 200 OK
Server: my-server/1.0
Content-Type: text/html
Content-Length: 1024

<html>
...
</html>
```

In this example, the server is responding with the HTTP/1.1 protocol, the status is 200 (OK), and it lists some headers followed by the content. In this case, an HTML document of size 1,024 bytes is returned. The headers in this case include the server, content type, and content length. The server is the name of the process that responded to the request.

The content type and length are meta-data about the response and may be used by the client to better handle the response. There are numerous different response status codes, but they fall into a few general categories such as: 1XX – Informational (i.e., 100 continue, or 101 Switching Protocols), 2XX – Success (i.e., 200 OK, or 206 Partial Content), 3XX – Redirection (i.e., 301 Moved Permanently, 302 Found, or 304 Not Modified), 4XX – Client Error (i.e., 404 Not Found, or 418 I'm a Teapot [42]), and 5XX – Server Error (i.e., 500 Internal Server Error, or 503 Service Unavailable). Client error responses occur when the client makes an error, i.e., requesting a page that does not exist, or for which they do not have authorization to access. A server error exists when the server fails to fulfill a valid request.

HTTPS

The secure version of the Hypertext Transfer Protocol is referred to as HTTPS [67]. A client connecting to a server via HTTPS must first establish a connection with the Transport Layer Security (TLS) protocol. After a TLS connection is established, it may send requests through that connection. HTTPS identifiers are slightly different from HTTP URIs, since they begin with '`https://`' instead of '`http://`'. With regards to our monitoring capability, we assume that a connection is providing HTTPS service if we see a TLS or SSL handshake on port 443. That means if HTTPS transactions occur on a nonstandard port, we do not count them.

2.2 Media Streaming

Media streaming over the Web has evolved with respect to how the content is provided and presented. Audio and video streaming services have recently undergone many changes with regards to the technologies driving them and the content itself. In this section, we will present a higher-level overview of media streaming and highlight several of the relevant technologies. We do not, however, go into detail about lower-level approaches such as encoding

algorithms. The technologies in use can improve user experience, assist with copyright law responsibilities, and assist service providers with content distribution.

2.2.1 Audio Streaming

Audio was the first type of media content to be streamed over the Internet. Audio streaming includes things such as: audio clips, music (both professionally made and amateur recordings), podcasts, and live-streaming radio-like services (such as a sportscast). Audio clips and podcasts are generally delivered as a static file (.mp3) from a Web site. Previously, various plugins may have been used to enable audio playback from the Web in an attempt to discourage piracy. For user-generated audio content, sites like SoundCloud are used, or a more popular (video) site such as YouTube is used. In this case, the music being uploaded would have a static image in the player on YouTube, and the content would arrive via mp3. Streaming music content is the most popular application of audio streaming.

The two most popular service models for music streaming are to provide some catalogue of content or a radio-like service. The difference between music streaming sites and radio-like services over the Internet is how the end user interacts with the content. On a music streaming site, the user may select songs and play lists from a list of content. A radio-like service, on the other hand, behaves like a radio broadcast. The content is chosen for you and is delivered 'live'; this includes things such as live sports commentating, news, and talk shows. Radio-like services are provided by users who set up an Internet radio station (with a service such as ShoutCast), and radio stations rebroadcasting over the Internet. The popular music streaming services (Spotify, Rdio, Google Play), offer both a catalogue of on-demand content as well as play lists. The play lists offered do not count as a radio-like service, since a user is able to skip or repeat songs.

2.2.2 Video Streaming

Video streaming has constantly evolved with regards to both the underlying technology used to deliver it, and the types of video available. Previously, video streaming was done with the use of third-party plugins such as RealPlayer, (Shockwave/Adobe) Flash, or Microsoft Silverlight, but there has been a shift away from using these types of plugins and towards using new features provided with HTML5. These features, in the form of a native 'VIDEO' tag, were designed with serving video content in mind. Sites like NetFlix and YouTube have already abandoned third-party plugins in favour of an HTML-only approach.

There are various video streaming services observed on campus that provide the users with different types of content. YouTube, Vimeo, and DailyMotion all allow for user-generated content to be uploaded. Hulu, Yahoo Screen, and NetFlix provide professionally-produced content. Twitch focuses mainly on live-streaming content – mainly of video games (YouTube has been expanding its live-streaming capabilities too). In this thesis, we will discuss NetFlix and Twitch in depth in Sections 2.5 and 2.6, respectively. We do not, however, characterize YouTube traffic in great detail, since YouTube has switched to using HTTPS by default.

2.2.3 Geo-Gating

Geographical gating (geo-gating) is when a service provider restricts access to content based on the user's location. When a client connects to a server that is geo-gating content, the server will determine where in the world the client's IP address is by querying a database or remote server. In this thesis, we observe this technology being used to restrict content due to licensing issues.

Users may try to bypass these restrictions. There are two main approaches used to bypass geo-gating. The first is to use a virtual private network (VPN), and the second is to use a third-party plugin. If a VPN is used, then traffic to and from the destination is sent through an encrypted tunnel. The other end of the tunnel in this case is in an area

where the content is not blocked, so the server sees all requests from the client (who is in a blocked area) coming from the unblocked end-point of the tunnel. In this case, since the tunnel is encrypted, we are unable to extract detailed application-level observations from the connection, such as what content is being requested and what request method is being used. When a third-party plugin such as Hola (a Web browser plugin) is used to access content, we are able to see the requests and responses that are sent over the Internet; no encryption is added. A third-party plugin generally works by re-routing (or proxying) some of the requests made by the browser (such as DNS requests) to get around the regional content restrictions.

2.2.4 Content Distribution Networks

A content distribution network (CDN) is a collection of servers distributed across the Internet. Content on a server is mirrored onto the others. The goals are to provide higher availability of content, since having a server fail will not make the content unreachable, higher performance, since the content may be closer to the end user, and improved scalability, since there are more servers to respond to requests. A CDN is useful since it may provide better service to the end user and requires less investment from the content provider (if using a third-party network).

We see various CDNs in use when inspecting traffic. These CDNs can be operated by the host organization, i.e., `cdn-vimeo.net` and `cdn-0.nflximg.com` (CDNs for Vimeo and NetFlix). A CDN may also be operated by a third-party provider, such as Akamai or Limelight.

2.3 Related Work in Traffic Measurement

There have been numerous studies focusing on the measurement and characterization of network traffic. We will group these studies into two broad categories: studies focusing on characterizing network traffic [10, 12, 13, 15, 16, 26, 41, 72, 81], and studies examining HTTP

traffic [40, 52, 63, 70, 71, 78].

Residential Internet usage was measured by Maier et al. [41] with a dataset from 2009 provided by a European Internet service provider (ISP). The study revealed that there was a shift away from peer-to-peer file-sharing applications and back towards HTTP traffic. Since the ISP provided DSL connections to its subscribers, the analysis focused on the consequences of this, such as IP reassignment, and short session length.

Chatzis et al. [12] measured traffic in 2012 from a major European ISP for 17 weeks. They found that many of the "critical Internet players" were trending towards homogeneous networks. That is, they host servers with the assistance of third parties or deploy massive numbers of their own servers.

Home networks were characterized in recent studies by Grover et al. [26] in 2013, and Xu et al. [81] in 2014. These studies found that there are strong diurnal patterns on home networks. They also provided empirical evidence of the popularity of YouTube and NetFlix.

Czyz et al. [16] studied denial of service attacks using the network time protocol (NTP) in 2014. They characterized many aspects of this type of attack, including the volume of traffic, number of devices, community response, etc. While this type of traffic is not the focus of the thesis, we have observed NTP exploitation on the University of Calgary's network. See Chapter 3 for our observations.

IPv6 adoption rates were also studied in 2014 by Czyz et al. [15]. They observed that adoption of the new addressing scheme is accelerating and that adoption is not geographically uniform. At the University of Calgary, we have observed very limited use of IPv6. In fact, all IPv6 traffic observed is currently tunnelled via IPv4.

Bustos-Jimenez and Fuenzalida [10] focused on measuring an ISP from the user's end to ensure that net-neutrality[1] rights are met. Their probes collected data between October 2011 and April 2012. They found that most ISP's provided less bandwidth to the consumer

[1]A basic description of net-neutrality is that an Internet service provider must treat all packets that it routes equally. No content is to be given priority over others.

than stated (i.e., a 10 Mbps plan would only give 8 Mbps). They also found that available speed varied depending on the time of day. During the night, the download speed would be much less than what the user's contract specified, indicating a policy-driven decision as opposed to an infrastructure failure. The system they developed was used by consumers to help defend their rights and enact positive service changes.

A study of machine-to-machine traffic by Shafiq et al. [72] focused on characterizing traffic from cellular devices. They used a week-long traffic trace from August 2011, and found that a majority of smartphone traffic was sent through TCP, and belonged to well-known applications (such as HTTP or email).

Chung et al. [13] studied mobile devices in enterprise networks using data from April 12-22, 2011. The found that across the three main smartphone OS's (Android, iOS, and Windows), there was significant use of mobile devices to transfer files, sometimes using peer-to-peer protocols such as BitTorrent. They also observed diurnal patterns with smartphone usage. Activities such as checking the news and weather would occur in the morning, and file transfers would occur overnight.

Newton et al. [52] conducted a long-term study of Web traffic from the University of North Carolina at Chapel Hill. This study used outgoing Web logs from a 13-year time period, from 1999-2012. They only counted traffic on TCP ports 80 and 443 (HTTP and HTTPS). Their analysis focused on packet headers. They were able to identify and characterize activity sessions. Their HTTPS analysis can count the number of connections in their traces and estimate how many requests and responses were exchanged (as well as their sizes) by comparing the sequence and acknowledgement numbers of the packet headers.

Mah developed an early model for HTTP network traffic [40] with data taken from late 1995. His model is based on the properties of request and response exchanges. The specific characteristics in his model are: request-length, response-length, document-size, think-time, consecutive document retrievals, and server selection. The model that Mah developed is

commonly used when studying static pages, or Web traffic in bulk. This type of model is not commonly used when characterizing video traffic. In the paper, Mah removes anomalous connections that poll a server every five minutes for new images. Video streaming (especially live-streaming) makes many connections at regular intervals, thus making video streaming connections unsuitable for this type of model.

Pries et al. [63] developed another model for HTTP traffic using statistics from many popular Web pages around the world. Their model used data from 2012 and shows that the number of embedded objects has increased, with images and scripts being the most prominent. They also found that the number of inline objects has greatly increased (when compared to past studies), and that much of the content is now being drawn from multiple originating servers. They expect that both of these counts (inline objects and embedded objects) will increase as HTML5 matures.

Schneider et al. [71] used data from residential networks in Europe, from 2008-2010, to examine some common pitfalls in the measurement of HTTP requests themselves. They found that there were three main classes of problems that arise when analyzing HTTP traffic: ignoring persistent/pipelined HTTP requests; content-type mismatches; and content-length mismatches. These issues are common across observed connections. We are able to observe some of these issues with our investigation of video traffic as well. See Chapter 4 for an explanation.

In 2009, Veres and Ionescu [78] proposed and demonstrated a measurement-based classification system for Web 2.0 applications. Web 2.0 applications include things like social media and video streaming. They were able to characterize instances of devices accessing these sites without using information above the transport layer. They found that video traffic volume dominates other traffic, and video traffic is transported by relatively few flows, compared to other applications such as photo album sharing.

HTTPS traffic flows were studied by Schatzmann et al. [70]. They looked specifically into

the classification of encrypted Web email traffic with an 11-day trace from March 2011. The approach taken by the authors was a passive one. They looked for email-related protocols across hosts that have similar client pools, identified known email servers, and then used the proximity to those servers to identify Web mail servers. After identifying the relevant servers, they characterized connections for their study.

2.4 Related Work in Video Traffic Characterization

Kuschnig et al. [38] examined request-response based HTTP streaming in 2011. By emulating a network, the authors found that the use of HTTP request-response streams is more robust than simple TCP streams for video transmission. In this case, a simple TCP stream is the transmission of the video file over a single TCP connection, where smooth playback can be achieved high over-provisioning. HTTP streams are better able to adapt to network conditions. Swaminathan [74] arrives at the same conclusion, namely that other protocols associated with streaming do not provide a good user experience. He states that HTTP-based streaming can be developed further to address these issues.

Dynamic adaptive streaming over HTTP (DASH) has been the subject of multiple studies [4, 36, 54, 64]. DASH is a popular approach to video streaming, which makes efforts to overcome the best-effort nature of the Internet. DASH is the basis of Apple's HTTP live-streaming (HLS), which is the service deployed by Twitch for their live-streaming solution. It also seems that DASH is used by NetFlix [66]. DASH works by breaking a single large video file into a sequence of many small video segment files that can be easily transmitted individually over the Internet. For example, if a DASH server wanted to serve a large file named *video.mp4* it would split the file into smaller files named *video-1.mp4*, *video-2.mp4*, ..., *video-N.mp4*; a client wanting to view *video.mp4* would request and play *video-1.mp4*, then *video-2.mp4*, and so on. A DASH server also provides the files in different levels of qual-

ity. Clients interacting with the server will automatically choose the best quality possible[2] (based on network conditions) and ask for the latest file in the sequence. With live-streaming content, if a file cannot be transmitted in time, it is skipped and the next one is requested.

Li et al. [39] examined techniques used from 1993-2013 to provide a retrospective view of the approaches and technologies used in video streaming. The overview described the previous approaches to streaming videos, both over HTTP and through other mechanisms such as peer-to-peer networks.

Plissanneau and Biersack investigated HTTP streaming for YouTube and DailyMotion from an ISP's perspective [58]. The dataset they use is composed of a set of ten one-hour traces captured between 2008-2011. They found that most video downloads fall into two basic groups: videos that are fully downloaded, and those that are not. The groups corresponded strongly to video quality (both delivery quality and content quality); i.e., bad video quality leads to early video cancellation. Another study by Din et al. [19] observed the same effect: poor connection quality as indicated by dropped packets may lead to shorter connection durations. An interesting observation was that even when the video quality was good, only half of the videos are fully downloaded, likely due to a lack of user interest.

Wei and Swaminathan considered the future of live-streaming video over HTTP 2.0 [80]. The authors primarily investigate the technologies that could be used in HTTP 2.0 (since HTTP 2.0 was not yet finalized [5]). One of the new features in HTTP 2.0 that may help with video streaming is the server push feature, which allows the server to proactively send data that has not yet been requested by the client. They found that this feature could reduce latency significantly.

In 2013, Tyson et al. [76] used a Web crawler to study a video site that specializes in pornographic content. With repeated use of the crawler, they were able to determine the popularity of videos within a certain time-frame. They also observed some characteristics that are present with other services, such as a small subset of the content being the most

[2]The user may request a specific quality level as well.

active. Unlike other video sharing sites, they found that popularity of a video rapidly decreases with time.

A study of student interaction with video streaming content was conducted by He [29]. He analyzed the messages that were sent (both online and offline) in an education service using data from the Fall 2009 semester. The chat analysis found that the primary use of the utility was to chat with other students, not to interact with the instructor.

Gill et al. [25] studied YouTube requests from the University of Calgary's network in 2007. This study was on video traffic sent from YouTube and the CDNs assisting it. There have been many changes since the study. First, YouTube's architecture has changed drastically, including a move to HTTPS. Second, the University's network has been upgraded since then. Finally, there are now many competing services available to choose from.

Metzger et al. [45] conducted an analysis of Web-based video delivery with YouTube in 2011. This study is more recent than the one by Gill [25], so it takes the infrastructure changes at YouTube into account. They did not measure at a network-level. Instead, they were more interested in video-playback characteristics, such as stalling time. Since these studies [25, 45], YouTube has switched to using HTTPS, making it impossible to exactly repeat this type of analysis, since the application-level details, such as content identifiers, are encrypted.

2.5 NetFlix

NetFlix provides TV shows and movies on-demand. The content provided by NetFlix is different from other video streaming sites, such as YouTube or Twitch, in several major ways. Specifically, NetFlix does not have user-generated content, content is often geo-gated, and NetFlix is a subscription-based service. NetFlix also does not have any support for live-streaming events.

NetFlix's model, i.e., providing only TV shows and movies, is important in differentiating

NetFlix from other services. Specifically, NetFlix does not offer other professionally-made content such as music videos, product overviews, or professional commentary for large events. YouTube and Yahoo Screen both offer these types of content. NetFlix has a mandatory subscription plan starting at $7.99/month[3]. This differentiates NetFlix from other services that offer movies and TV shows, like Yahoo Screen (no subscription) and Hulu (optional subscription).

Hulu also provides similar content (movies and TV shows) with both a free and premium service, but is not available in Canada. NetFlix's geo-gating is an important characteristic. Not all content on NetFlix is globally visible. That is, some content provided in the United States may not be available in Canada or the rest of the world, and vice versa. Unlike Yahoo Screen, NetFlix does not list the unavailable content[4].

2.5.1 History

When NetFlix was founded in 1997, it provided an online interface to a DVD rental service [51]. This service is still available in the United States. Starting in 2007, NetFlix started to provide online streaming of content in the United States, and expanded this service into Canada in 2010. When NetFlix started to offer streaming services over the Web, they first used Microsoft's Silverlight plugin for digital rights management (DRM) related purposes, but more recently (in 2013) they have switched to using HTML5. In 2011, NetFlix expanded into South America and Latin America, and in 2012 they began to expand into Europe. NetFlix also started to provide original content to subscribers in 2013 with their release of *House of Cards*[5], and a new season of *Arrested Development*.

[3]The $7.99/month plan allows for up to two devices to be used at once with HD (1080p) streaming. There is also a $11.99/month plan that allows four devices and Ultra HD (4k) streams.

[4]Yahoo Screen produces and is the only distributor of season 6 of Community, but the content does not play in Canada.

[5]The NetFlix original series House of Cards is based on a previous BBC series of the same name.

2.5.2 Related Work

Many of the previous studies [1, 2, 65, 43] involving NetFlix traffic do not reflect some of the recent technical changes.

Studies done by Adhikari et al. [1, 2] studied how NetFlix connects to various clients across the United States with data traces from 2011. The technical details, including hostnames, usage of CDNs, and usage of SilverLight, have all changed since the study was published.

NetFlix traffic volumes were studied by Martin et al. [43] in 2013. This study was done in 2013, when NetFlix was using third-party CDNs to deliver video traffic. They observed that NetFlix's implementation of DASH defaults to TCP congestion control mechanisms when the network is under heavy traffic.

Streaming behaviour of NetFlix and YouTube on the client's end was also studied by Ito et al. [33] in 2014. This study determined some network-level characteristics of the traffic in many scenarios. They found that the NetFlix player consumes an average of 3.4 Mbps – YouTube consumed around 1.2 Mbps. The behaviour of a NetFlix connection differed from YouTube: NetFlix uses a period of high bandwidth at first to fill a buffer, then reduces to a much lower level of bandwidth. This study was done in June 2014, after NetFlix switched to HTML5, but another study by Rao et al. [65], in 2011, showed similar behaviour with the Silverlight plugin.

2.6 Twitch

Twitch is a site that is focused on live-streaming of video game content. The content on Twitch is focused on video games or other types of non-sports games, such as board games or card games. Twitch provides live-streaming capabilities as well as video on demand (VOD) capabilities for past broadcasts. Twitch does not have a mandatory subscription fee, nor does it geo-gate content. However, Twitch allows users to pay an optional monthly subscription fee (to Twitch or streamer(s)) for some benefits; this is described in Appendix F. Unlike

YouTube, a Twitch streamer may not upload pre-recorded videos. Twitch currently uses Flash on the user's end to stream videos.

Twitch, due to its content, is very different from other services like NetFlix or YouTube. Twitch focuses on live-streaming video games and provides some utilities to help the streamer interact with the viewers. Every live-stream on Twitch also has a 'chat' associated with it (a Web embedded Internet Relay Chat (IRC)). The chat allows users to converse with the streamer and amongst themselves about the content. Twitch primarily organizes live-streams by game title. On the homepage, there are also listings for the top channels being broadcast from gaming consoles (XBox One, PlayStation 4), but the console streams are much less popular than the other ones (much fewer viewers).

2.6.1 History

Twitch started in 2011 as a self-sufficient spinoff from the more general streaming site `JustinTV.com`[6]. Twitch was acquired by Amazon in September 2014. One of Twitch's earliest competitors, `Own3d.tv`, failed in early 2013 after controversy surrounding its business practices [44]. The `own3d.tv` domain is still active today, but completely unaffiliated with the original service. Twitch currently has a virtual monopoly on all video game streaming events [59]. YouTube and DailyMotion are both trying to gain traction in video game live-streaming, but have had limited success so far.

2.6.2 Related Work

Shea et al. [73] conducted a study of Twitch's streaming service focused on streaming software. They were specifically investigating Open Broadcast Software (OBS) – a popular program used to send streams to Twitch. Their experiments with this software occurred in 2015. This study did not investigate network events, but instead profiled the workload of a streaming computer.

[6] JustinTV was active from 2007-August 2014.

Hamilton et al. [28] characterized the Twitch community itself in 2014. The authors of this study focused on the social aspects of the community as well as what environment Twitch presents (in a social context). This study was able to get some information from a variety of streamers (on both big and small channels) about the social interactions they have.

The community that surrounds Twitch was studied by Nascimento et al. [48]. They specifically targeted streamers involved in eSports for the game Star Craft 2 (SC2) from October 2014 to February 2015. Their observations were based on interactions in Twitch chat. They found that viewers displayed certain behaviours, such as channel surfing and early exit (leaving a stream a few minutes before it was ending).

Twitch traffic was studied recently by Zhang and Liu [84], using data from the Twitch API. They crawled Twitch in the fall of 2014 and found most viewers watch from a desktop as opposed to a console device such as an XBox or Playstation. When examining the streamers themselves, they observed that less than 1% of them triggered 70% of the views. Strong diurnal patterns from these streamers was also observed.

A comparison of Twitch and YouTube's live-streaming capabilities was conducted by Pires and Simon [57] from January to April 2014. In this study, they found that Twitch is a more mature system, with many more concurrent channels and sessions than YouTube. The authors also conducted another study on Twitch's use of DASH [56].

Another study with data obtained from crawling Twitch was done by Kaytoue et al. [34] taking place from the end of September 2011 to the start of January 2012. This study focused on the community around Twitch, with a special interest in the eSports community. They found that many streams (41%) originate on the west coast of North America, 19% on the East coast, and the rest were mostly from Europe or south-east Asia and Korea. They also observed fluctuations in game popularity. These fluctuations occurred when a new game was released; that is, new games receive a surge of popularity.

2.7 Summary

In this chapter, we described the TCP/IP protocol stack, and approaches to media streaming for both audio and video content. We surveyed related work in the areas of network traffic measurement and video traffic. Finally, we described the two main services we will study, NetFlix and Twitch, and summarized previous studies done with these services. Our study with these two services is novel since we are using a large network-level dataset.

In the next chapter, we will describe the tools and methodology used to collect our dataset, as well as the characteristics of traffic on the University of Calgary's network.

Chapter 3

Measurement Methodology

Our data is collected from a mirrored stream of all traffic that passes through the University of Calgary's edge routers. This means that we can observe all traffic that has one endpoint in the Campus network and the other endpoint in the Internet.

We use a Dell server to monitor the mirrored traffic stream. This server is equipped with two Intel Xeon E5-2690 CPUs (32 logical cores @2.9 GHz) with 64 GB of RAM and 5.5 TB of local storage for logs. The operating system on the server is CentOS 6.6 x64. We backup the logs nightly to a file server with more storage. Our monitoring server uses an Endace DAG 8.1SX capture card with the firmware updated to the latest release (March 2013) to capture the mirrored traffic. The features of this card will be detailed in Section 3.1.

We run a custom tool to collect aggregate throughput information about the traffic, such as TCP or UDP bytes in and out. Section 3.1 has more information about this tool. In addition, we run the Bro Network Monitor [55] to collect connection-level logs about all traffic that we see. Section 3.2 has more information on our specific usage of Bro. We have the capability to use other tools to analyze the traffic stream, as described in Section 3.3.

3.1 Network Throughput

The Endace card in the server is capable of filtering, steering, and splitting traffic across many different streams. The tool that we use to log network throughput information is written in C and uses the Endace DAG API. Using the API, we are able to look at incoming packets and read header information, i.e., IP version, IP addresses, protocol number, and packet length. This information is aggregated and logged at one-minute intervals to give us network usage information.

We chose to use our own tool to collect this information for several reasons. First, other throughput tools available were not written for the DAG API. Second, the program is simple, robust and lightweight. Third, it is an independent way to validate summary results in Bro. We can partially reconstruct this throughput information using Bro's connection logs, but we may miss information for a couple of reasons. First, connection log entries do not have any way to determine how packets in a connection were delivered over time, so when reconstructing throughput information, we assume all connections send/receive bytes uniformly over their duration. For example, we assume that if a connection lasts two minutes and sends two megabytes, then it sent one megabyte per minute. A second issue is that Bro only logs connections when they terminate, so if we wanted to get throughput information for a specific day, we may miss connections that extend beyond the end of the day[1].

3.2 Bro

Bro is an open-source network security monitor [55]. By default, Bro records connection events observed on an interface or from a pre-recorded packet capture file. The logs that Bro produces that are of primary interest to us are the connection, HTTP, and SSL logs. The connection logs list general information about each observed connection, i.e., start time, endpoints, bytes/packets transferred by each endpoint, duration, termination-state. The HTTP logs contain information about each HTTP request/response pair, with information such as start time, endpoints, request/response body length, domain, path, referrer, etc. We have extended Bro's default behaviour to collect extra information about HTTP request-response transactions. This extra information includes request and response start and end times, as well as some select headers from the messages, such as cache policy and response type. The SSL logs contain information about encrypted connections. We use the SSL logs to identify connections that communicated with servers of interest, i.e., NetFlix authentication

[1]We found that some connections lasting multiple days were the result of network misuse.

servers, or GoogleVideo servers.

Using the information available in all the logs, as well as some other sources, we can gain a general understanding of the usage of the University of Calgary's network. See Section 3.4 for details.

The traffic splitting feature of the Endace card is used for load balancing in our deployment.

3.3 Other Collection Tools

With our configuration of the server, we can use other tools to process the traffic stream as well. We have occasionally used `tcpdump` to look for specific traffic in the live-stream (i.e., NTP traffic). We also have occasionally used the Endace tool `dagsnap` to collect full-packet traces, which are used for debugging purposes. `dagsnap` is capable of capturing all traffic on the interface with no packet losses. Other tools that can be used on the server include any that use the DAG API or libpcap, since we have compiled libpcap on the server with DAG support.

3.4 Traffic Overview

Over the five months that we collected data from the Campus network, we have measured over 2.7 PB of traffic. We observed numerous general trends in usage as well as some anomalies in this traffic. We have produced throughput graphs with the information produced by the tool described in Section 3.1. These graphs show inbound and outbound throughput levels (in gigabits per second) split across the X-axis for various protocols. The most visible protocols are TCP (in blue), and UDP (in yellow). When comparing traffic from December 2014, in Figure 3.1, with traffic from the end of April 2015 in Figure 3.2, we notice that there was a significantly higher level of outbound UDP traffic in December. This UDP traffic was due to a Network Time Protocol (NTP) exploitation attack. We examine UDP traffic in

Appendix A.

Our traffic follows a diurnal pattern that corresponds to when the majority of people are on campus. The busy period starts in the late morning with usage peaking mid-day and continuing until the late evening. The idle period starts late in the night and lasts until the morning. The peak inbound rates approach 2.5 Gbps, consisting mostly of TCP traffic. Our outbound traffic (excluding UDP-based NTP exploit traffic) is under 1 Gbps. The levels of traffic dip slightly over the weekends and are much lower when there is an academic break in the University's calendar.

3.4.1 Outages

Our collection period for Bro logs starts on December 1, 2014 and runs until April 29, 2015. We missed collection with the throughput tool for the first week of December. Several outages were due to power or network outages on Campus, or they were caused by issues with our server configuration. The following are lists of interruptions:

Network/Power Interruptions

- January 30, 2015, 11:19-12:12 – power failure
- April 29, 2015 – full traffic mirror disconnected

The mirror disconnect corresponds to the end of our collection period.

Bro Interruptions

- December 22, 2014
- December 23, 2014, 00:00-11:15
- February 15, 2015, 18:00-19:00
- April 10, 2015, 10:00-24:00
- April 11, 2015

- April 30, 2015, 02:00-24:00

Throughput tool failures

- January 30, 2015, 11:19-February 2, 2015, 10:17
- April 30-May 1, 2015

The throughput tool failure from January 30 – February 2 was caused by a misconfigured startup script that was triggered by the power outage. On April 29, 2015, a misconfiguration in the network resulted in our traffic mirror being disconnected. The cause of the throughput tool's failure after our mirror was disconnected on April 29th is unknown.

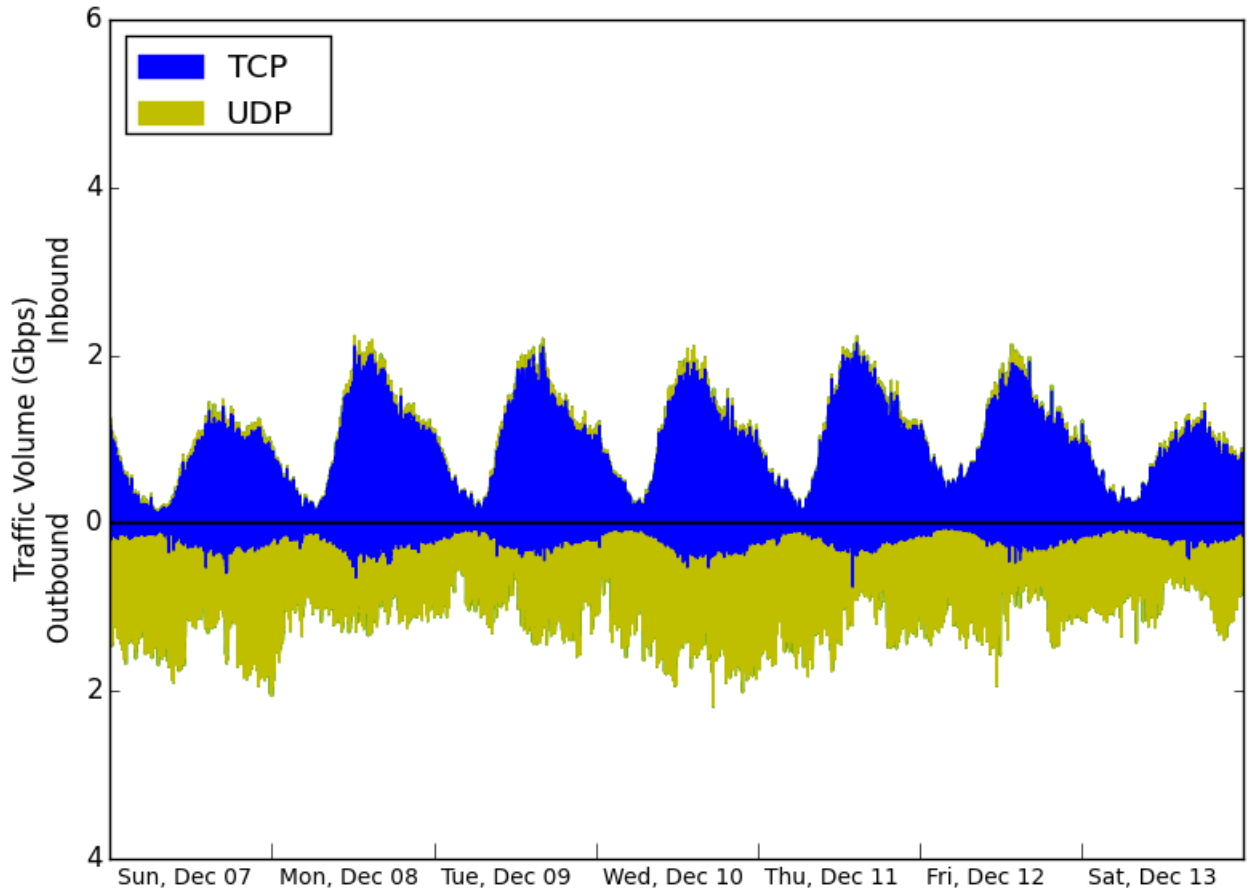


Figure 3.1: Campus Network Traffic, December 7-13, 2014

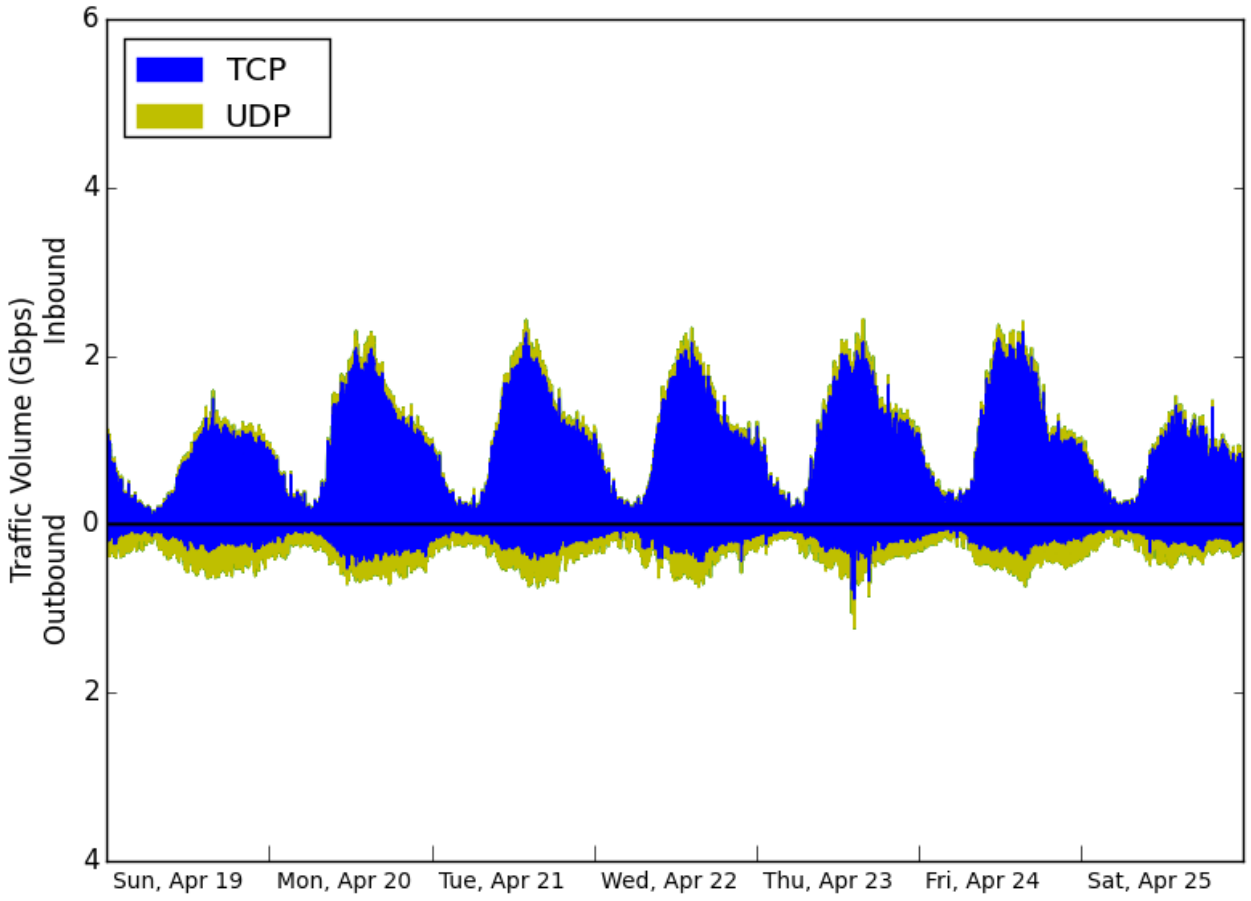


Figure 3.2: Campus Network Traffic, April 19-25, 2015

3.4.2 TCP

Out of the 2.7 PB traffic, 1.75 PB was TCP, and the remaining 0.95 PB was UDP (UDP is discussed in Appendix A). There is much more inbound TCP traffic than outbound traffic; 1.40 PB in and 0.35 PB out over the five-month period. This is expected, since it corresponds to users on campus retrieving information from servers like Google (including YouTube), and Facebook. Inbound traffic is primarily composed of HTTP traffic (TCP port 80), or HTTPS traffic (TCP port 443). Not all traffic flows on TCP ports 80 and 443 are necessarily HTTP(s) connections, since they may include things such as scans or upgraded (WebSockets) connections. Monthly breakdowns of traffic volumes are shown in Figure 3.3.

The inbound TCP traffic that we see is mostly HTTP(S) traffic. The inbound traffic in

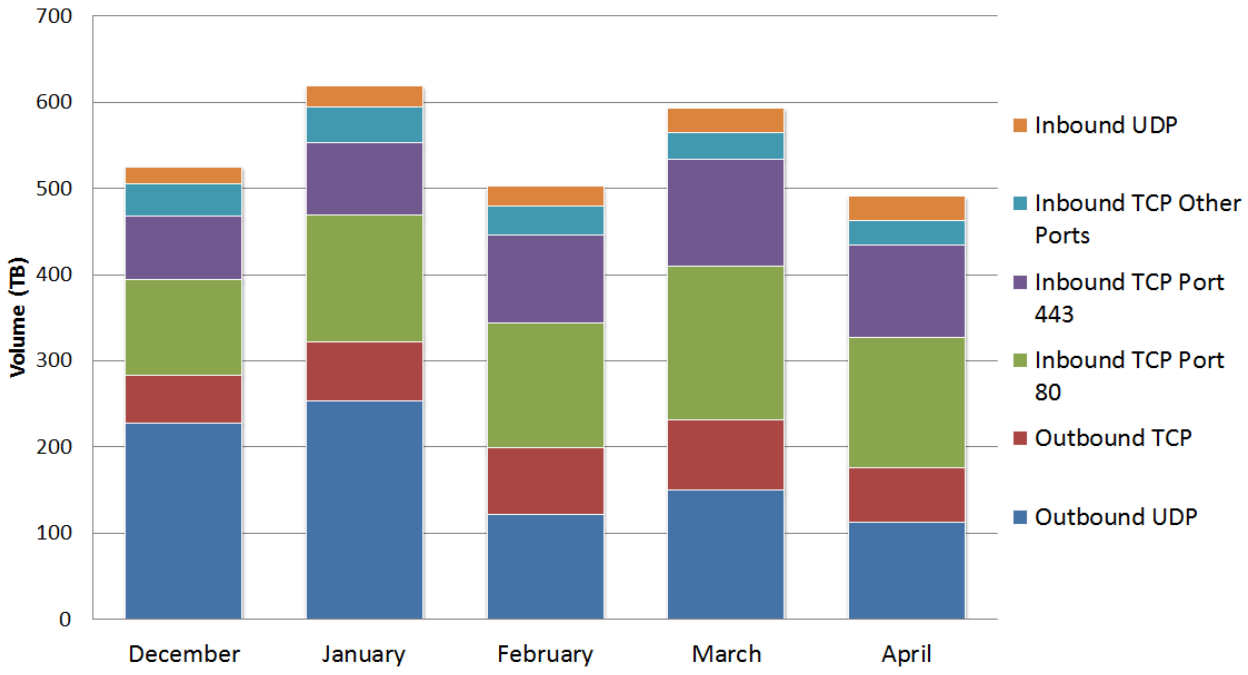


Figure 3.3: Monthly Traffic Breakdown

these counts includes both responses to requests originating from campus and requests to campus Web servers from the Internet. In fact, over 80% of inbound TCP traffic is HTTP(S); see Table 3.1 for monthly breakdowns.

Table 3.1: Inbound TCP Traffic Breakdown

	HTTP		HTTPS		Total
	Volume	Percent	Volume	Percent	Volume
December	111.4 TB	50.1%	73.59 TB	33.1%	222.4 TB
January	147.2 TB	54.1%	83.73 TB	30.8%	272.2 TB
February	145.2 TB	51.7%	101.8 TB	36.2%	281.0 TB
March	178.0 TB	53.5%	124.8 TB	37.4%	333.8 TB
April	151.7 TB	52.9%	107.3 TB	37.4%	286.6 TB

HTTP

As stated previously, not all connections on ports 80 or 443 are HTTP(s) connections. Some of these connections are caused by scanning activity or they may be used by other applications, such as BitTorrent, in order to bypass firewalls (i.e., masquerading). No HTTP requests or responses are transmitted (correct behaviour) with these connections. However,

we have observed that some connections that immediately upgrade to a (secure) WebSockets[2] connection do not receive the HTTP label from Bro, since they do not send a visible HTTP request. Due to this behaviour, we are unable to track certain connections of interest, including Twitch Chat connections (Twitch Chat is described in Appendix G).

Over the collection period, we observed over 10.5 billion HTTP requests with a total response body length of 726.68 TB (from both servers on campus and on the Internet). Table 3.2 shows a percentage breakdown of the most popular request methods and status codes seen for the entire collection period. There were many HTTP transactions that had no associated method. It's possible that some transactions were not properly logged as their attributes for requests and responses were empty in the HTTP logs. Some transactions received a 400 Bad Request response (semantically correct behaviour), but it seems like many of these transactions are parts of web applications. For example, many of these transactions were sent to NetFlix's streaming services and received a 206 Partial content response, we believe these transactions were caused mainly by mobile devices. There were also some transactions that sent a few kilobytes in their request (with no method) and received no response.

Table 3.2: HTTP Summary Information

Request Method		Status Code	
Method	Percent	Code	Percent
GET	90.6%	200 (OK)	76.6%
POST	6.4%	302 (Found)	7.0%
HEAD	1.2%	304 (Not Modified)	4.8%
Other	0.2%	206 (Partial Content)	2.2%
None	1.6%	204 (No Content)	1.7%
		404 (Not Found)	1.1%
		Other	3.5%
		None	3.1%

Inbound HTTP traffic from servers on the Internet measured 642.1 TB with 9.4 billion request-response pairs. Table 3.3 shows the top content type headers used throughout our

[2]The WebSockets protocol allows bi-directional communication between a server and client.

observation period for inbound traffic. A total of 81,876 unique content-type headers were seen. With this table, we can see that a low number of requests does not imply a low number of bytes transferred. When checking the entries in the Bro HTTP logs, we can see that in many cases the content-header type does not match the response MIME type; we get many occurrences where the mismatch is minor, i.e., the content type is `Text/html` but the MIME type is `Text/plain` or vice versa.

Table 3.3: HTTP Inbound response content type headers

Type	Volume	Percentage of Requests
`Application/octet-stream`	310.14 TB	5.15%
`Video/mp4`	63.81 TB	0.55%
`Image/jpeg`	33.02 TB	11.82%
`Video/mp2t`	30.83 TB	0.35%
`Text/plain`	23.00 TB	5.93%
`Video/x-flv`	17.27 TB	0.07%
`Text/html`	14.54 TB	17.53%
`Image/gif`	14.02 TB	12.91%
`Video/f4f`	13.89 TB	0.29%
`Application/x-steam-chunk`	13.82 TB	0.32%
`Video/*`	9.98 TB	0.41%
Other	95.53 TB	33.43%
None	2.52 TB	11.06%

`Video/*` excludes explicitly stated types

The responses with `Application/octet-stream` set as their type are either software updates from companies like Apple[3] or Microsoft[4], content from Amazon's cloud, or more commonly, video being transported from NetFlix.

Video content is most often served via CDNs. The popular CDNs that we have observed include: Twitch (`twitch.com` or `ttvnw.net`), third-party CDNs (such as Akamai or Cloudfront), Google (`googlevideo.com` and `2mdn.net`), and various different CDNs directly associated with pornographic content. Another type that we commonly see, Flash[5], is not

[3]From the domains: `swcdn.apple.com`, `phobos.apple.com`, or `appldnld.apple.com`.

[4]From the `download.windowsupdate.com` domain.

[5]The common content types for Flash are: `Application/x-fcs`, `Application/flv`, `Application/x-flv`, or they start with `Flash/`.

as common as it was in the past. We mostly see Flash videos being used to show ads on the Internet. These ads are either requested from a CDN or from companies or domains directly associated with advertisements.

The `Application/x-steam-chunk` type is used by Steam, a digital storefront for video games. Steam, by default, automatically updates any games a user has downloaded.

The most popular external domains (by traffic volume) that we see over our observation period are listed in Table 3.4. Note that this table measures only the HTTP traffic.

Table 3.4: Top 20 HTTP Server Domains by Traffic Volume

Host	Volume	Percent	Description
`netflix.com`	217.10 TB	33.81%	Video streaming, see Chapter 5.
`apple.com`	53.75 TB	8.37%	Operating system and software updates, iTunes store and associated services.
`googlevideo.com`	15.59 TB	2.43%	Video streaming, unencrypted YouTube traffic.
`steampowered.com`	13.73 TB	2.14%	Software downloads.
`twitch.tv`	13.12 TB	2.04%	Live-streaming videos, see Chapter 6.
`akamaihd.net`	11.93 TB	1.86%	Third party CDN.
`instagram.com`	10.44 TB	1.63%	Social network operated by Facebook that specializes in sharing photos (on mobile).
`imugr.com`	7.71 TB	1.20%	Photo sharing site
`tumblr.com`	7.71 TB	1.20%	Blogs.
`ttvnw.net`	6.37 TB	0.99%	Domain operated by Twitch to stream videos.
`windowsupdate.com`	5.66 TB	0.88%	Operating system updates.
`google.com`	4.58 TB	0.71%	Google it.
`9c9media.com`	3.80 TB	0.59%	Registered to Bell Media Inc.
`rndcn3.com`	3.56 TB	0.55%	Associated with pornography.
`amazonaws.com`	3.39 TB	0.53%	Amazon Web Services.
`dailymotion.com`	3.23 TB	0.50%	Video Streaming service.
`llnwd.net`	3.22 TB	0.50%	Limelight networks.
`spotify.com`	3.20 TB	0.50%	Music streaming service.
`edgesuit.net`	3.08 TB	0.48%	Associated with Akamai.
`musicnet.com`	3.08 TB	0.48%	Third Party CDN.
Subtotal	394.25 TB	61.50%	

Percent of Inbound HTTP volume (642.1 TB)

As Table 3.4 shows, no single domain (excluding NetFlix[6]), accounts for a significant portion of HTTP traffic. This indicates that there are many different domains serving HTTP content to campus. In fact, over our observation period, we observed over 1.90 million

[6]Traffic levels for NetFlix include traffic from IP addresses owned by NetFlix. See Appendix D for a list.

unique domains. In this domain count, we group domains to the highest level we can, i.e., `image.google.com` and `plus.google.com` are grouped into `google.com`, while `google.ca` is excluded in this case.

HTTPS

Similar to the issue with tracking HTTP traffic, not all connections to port 443 are HTTPS, since there may be scanning connections or other applications using the ports to bypass firewalls. We may, however, use the SSL logs that Bro produces to identify HTTPS servers, since the SSL log lists the server name associated with certificates that it sees. The downside to this approach is that it becomes much harder to find out how much traffic was exchanged, since there are many server names used and the SSL log does not list bytes exchanged in connections.

By using the same grouping strategy as we did for HTTP domains, we can once again aggregate sub-domains for popular services on the Web. When doing this, we can easily find how often a server is contacted. We have counted 3.97 billion connections from over 5.59 million different domains in the SSL logs. The most popular external SSL servers are listed in Table 3.5. Note that we chose to order by connections instead of volume since Bro's SSL logs, which list server names, do not list bytes transferred.

A strange entry in our SSL logs was `majuwe.com`, a domain associated with ad-ware. We found that a single local machine was responsible for almost all the connections to the domain. This domain is being hosted on a third-party CDN, so looking for more information, such as the owner, based on an IP address does not result in more information. It also means that attempting to block the domain at a network level does not work, since the CDN will use another IP address for connections.

There was also a significant number of servers, with over 626 million connections (15.8%), that had an empty name in the SSL log. We are able to uniquely identify these servers with their IP addresses. We counted over 208,000 external devices that do not have a name in the

Table 3.5: Top 10 HTTPS Server Domains by Connections

Host	Connection Count	Percent	Volume	Description
google.com	314 million	7.91%	27.3 TB	Popular non-YouTube Google services.
apple.com	179 million	4.51%	2.8 TB	Apple services.
majuwe.com	168 million	4.23%	106.7 GB	Domain associated with ad-ware.
akamaihd.com	151 million	3.80%	32.7 TB	Third party CDN.
googlevideo.com	131 million	3.30%	230.1 TB	Video streaming on YouTube.
facebook.com	130 million	3.27%	18.6 TB	Social network.
icloud.com	88.0 million	2.22%	546.4 GB	Apple could storage.
gstatic.com	88.0 million	2.22%	7.8 TB	Static elements from Google - Javascript, CSS, etc..
live.com	74.0 million	1.86%	5.9 TB	Microsoft personal email service.
microsoft.com	72.3 million	1.82%	3.0 TB	Microsoft services.
Subtotal	1.40 billion	35.25%	328.8 TB	66.94% of HTTPS Traffic.

SSL log. Using a bulk whois resolver[7], we were able to resolve all but 398 addresses. 78% of these requests belong to five organizations:

1. Apple - 115 million connections (24%)
2. Google - 95 million connections (19%)
3. Microsoft - 77 million connections (16%)
4. Facebook - 47 million connections (10%)
5. Amazon - 45 million connections (9%)

HTTPS traffic should mirror normal HTTP traffic characteristics. That is, the content-type being transported has a much greater influence on bytes transferred than the number of connections. This characteristic allows us to assume that the domains associated with `googlevideo` transmit more traffic than the others, as we will see in Chapter 4.

[7] `www.team-cymru.org`

3.5 Summary

In this chapter, we described our monitoring capabilities and the tools used to gather data. We summarized our collection period and interruptions encountered during this period. Finally, we provided a basic overview of traffic characteristics observed during this period.

In the next chapter, we will go into greater detail about video traffic levels and characteristics seen during our five-month collection period.

Chapter 4

Video Traffic Analysis

In this chapter, we investigate inbound video traffic. As stated previously in Chapter 3, the three most common content-type headers used to transport video are `Video`, `Flash`, and `Application/octet-stream`. Together, these three types accounted for 432.9 TB (67.42%) of inbound HTTP traffic. In Section 4.1, we characterize the different content types and external domains observed serving video over HTTP. Section 4.2 shows the characteristics of Flash content. Octet-stream content is summarized in Section 4.3. Finally, in Section 4.4, we show how the traffic volumes from two popular HTTP providers, NetFlix and Twitch, as well as YouTube (including HTTPS), compare to the overall inbound HTTP and HTTPS traffic.

We occasionally see some other content types used to transport video content, such as `Application/x-silverlight-app`, or `Application/vnd.apple.mpegurl`. The Silverlight plugin from Microsoft was used before HTML5 to stream media that needed DRM protection. Over the collection period, we have observed that only 29 GB ($< 0.01\%$ of inbound HTTP) of data had the `silverlight-app` content-type. The `apple.mpegurl` content type is used in Apple's HLS service (that we see in use by Twitch); we have seen 191 GB (0.03% of inbound HTTP) of this type of content sent over our collection period. Since the volumes for these other types of content are low, we will not focus on analyzing this type of traffic.

4.1 Video Content

In this section, we investigate the inbound HTTP traffic that had a '`Video`' type content header. We counted over 123 million request-response pairs for HTTP video content responsible for 104.0 TB (16.20%) of inbound HTTP traffic (6.85% of total inbound traffic). This

does not include traffic over HTTPS that is likely transporting video, which we will review in subsection 4.4.1. There were 111 different types of video tags seen. A majority of bytes were transported with only a few different video tags, as shown in Table 4.1.

Table 4.1: HTTP Video Types

Type	Volume	Volume Percent	Percent of Video Requests
`Video/mp4`	63.81 TB	61.36%	41.80%
`Video/mp2t`	30.83 TB	29.64%	26.68%
`Video/x-m4v`	5.65 TB	5.43%	0.14%
`Video/webm`	1.52 TB	1.46%	1.36%
`Video/quicktime`	0.41 TB	0.39%	0.08%
Others	1.75 TB	1.68%	29.91%

Requests with the content-type of `Video/webm` are gaining in popularity; this is because `Video/webm` content is replacing `Image/gif` content on popular sites. We have also seen entries in the Bro HTTP logs that have the content type set to '`Video`' and have an empty response MIME type. We investigate the external servers that provide video content in the following sub-section.

4.1.1 External Video Domains

This section investigates the domains that serve video content to users on campus. Our count for external video servers includes responses with the content types `Video/f4f` and `Video/flv`; that is, any content type beginning with '`Video`' is counted for the following analysis. These responses had a total response-length of 124.9 TB.

Named Hosts

Over our collection period, we observed 16,700 domains serving video content, with over 148 million requests.

Table 4.2 shows the popular HTTP video services. In this table, Twitch includes all of its associated domains: `twitch.tv` (13.07 TB, 13.7 million connections), `ttvnw.net` (6.33 TB, 7.4 million connections), and `justin.tv` (0.31 TB, $< 10,000$ connections). Twitch's charac-

Table 4.2: Popular HTTP Video Services

Service	Volume	Percent	Connections
twitch.tv	19.72 TB	15.8%	21.1 million
akamaihd.net	11.49 TB	9.20%	56.6 million
youtube.com	9.19 TB	7.36%	6.87 million
apple.com	5.21 TB	4.17%	259,000
neulion.com	4.96 TB	3.97%	6.12 million
instagram.com	4.96 TB	3.97%	10.0 million
9c9media.com	3.76 TB	3.01%	3.38 million
rncdn3.com	3.56 TB	2.85%	1.29 million
dailymotion.com	3.22 TB	2.58%	2.84 million
xvideos.com	2.29 TB	1.83%	1.20 million

teristics are described in Chapter 6. The Akamai CDN is the most popular CDN observed, and has an edge-node located in the data-center on the University campus. The numbers for YouTube include `googlevideo.com`, which sent 8.39 TB over 5.91 million connections, and `youtube`, which sent 0.80 TB over 0.96 million connections. These counts exclude HTTPS traffic.

The rest of the entries in Table 4.2 are described as follows. The video traffic from Apple was likely promotional materials for products and streams of Apple events. Neulion provides live and on-demand video broadcasting over the Internet, for major sports leagues such as the NHL. Instagram is a photo and video sharing social network. `9c9media` is registered to Bell Media Inc. We believe that `rncdn3.com` is associated with pornography, since Bro logs commonly list the referrer to these video requests as a porn streaming site. DailyMotion is another video streaming service. Finally, `xvideos.com` is a pornographic video streaming service.

IP Hosts

When inspecting our HTTP logs generated by Bro, we observed over 11,200 external hosts serving video content without a Host-name. They transferred 10.84 TB of data in over 5.00 million requests.

Table 4.3 shows the popular subnets observed for unnamed HTTP video content servers.

Table 4.3: Unnamed HTTP Video Host subnets

Subnet	Volume	Percent	Connections	Operator
50.7.164.0/24	1.055 TB	9.73%	28,400 connections	FDC Servers (Amsterdam)
63.243.196.0/24	1.041 TB	9.60%	250,000 connections	Tata Communications (America) Inc.
23.236.121.0/24	0.516 TB	4.76%	115,000 connections	C3 Networks Inc.
65.255.35.0/24	0.482 TB	4.45%	123,000 connections	C3 Networks Inc.
70.39.188.0/24	0.394 TB	3.64%	361,000 connections	Packet Exchange Inc.

These subnets are associated with enterprise data-centers or ISPs.

4.2 Flash Content

Over the collection period, we observed 36.81 TB (5.73% of inbound HTTP) of Flash content, with over 298 million requests. There were 44 different types of Flash content tags; the most popular of these are shown in Table 4.4.

Table 4.4: HTTP Flash Types

Type	Volume	Volume Percent	Percent of Flash Requests
`Video/x-flv`	17.27 TB	46.92%	2.31%
`Video/f4f`	13.89 TB	37.73%	9.21%
`Application/x-shockwave-flash`	3.67 TB	9.97%	20.70%
`Application/flv`	0.81 TB	2.20%	0.01%
`Video/flv`	0.63 TB	1.71%	0.16%
`Application/x-fcs`	0.24 TB	0.65%	67.58%
Others	0.05 TB	0.14%	0.30%

Unlike responses with a `Video` content-type, Flash responses are skewed. Responses with `Application/x-fcs` account for a majority of Flash requests (202 million), but account for less than 1% of bytes. This type of content is actually associated with audio streaming; we commonly see it used for radio over the Internet. Flash `flv` and `x-flv` content are commonly used for displaying embedded clips (such as sports highlights), or are served from smaller services such as dailymotion or from pornographic video sites. Flash `f4f` content is most commonly served from a CDN such as Akamai or one operated by the organization (i.e., `videocdn.vice.com`). Shockwave-flash content is mostly served from domains associated

with advertisements, such as `adap.tv` or `quantserve.com`, thus we can safely assume that they are ads.

IP addresses in the 68.142.64.0/18 subnet were responsible for serving over 90% of all Flash requests; this subnet is operated by the Limelight CDN.

4.3 Octet-stream content

Octet-stream content accounts for 311.4 TB (48.5%) of inbound HTTP traffic, with over 486 million requests. As previously stated, not all content with "`octet-stream`" in the content-type header is video traffic. There were 62 different types of responses that were some form of (non-text) octet-streams. The most prevalent types are listed in Table 4.5.

Table 4.5: HTTP Octet-Stream Types

Type	Volume	Percent of Requests
`Application/octet-stream`	310.14 TB	99.57%
`Binary/octet-stream`	0.98 TB	0.38%
Others	0.28 TB	0.06%

As stated in Chapter 3, a significant portion of `Application/octet-stream` content is actually software updates from companies such as Apple and Microsoft. The traffic that we can identify as video traffic using this content type comes from NetFlix, Google (via `googlevideo.com`), Baidu (a Chinese search engine), wimp (curated video content), and uStream (streaming service). NetFlix was the source of 217.1 TB (69.72%) of octet-stream content; we will discuss NetFlix traffic in Chapter 5. We also see content from CDNs such as Akamai and Cloudfront that may be video. Additionally, we have seen some ads delivered with `Application/octet-stream` through domains such as `tubemogel.com`. The `Binary/octet-stream` content seems to be software updates or connections to an online multi-player game (e.g., EVE Online).

4.4 Video Traffic

Table 4.6 shows HTTP traffic volumes to various video services by month. The level of unencrypted traffic generated by these video services is low. Yahoo Screen, a service that we previously mentioned, serves no unencrypted video traffic. Vimeo delivers video by its own CDN (`vimeocdn.com`), or using a third-party CDN, such as Akamai (`vimeo.<node>.akamaihd.net`). The volumes for Vimeo in Table 4.6 contain traffic from Vimeo's CDN as well as the nodes operated by Akamai. The unencrypted traffic levels for YouTube are low, but as we have previously mentioned, YouTube serves a majority of its traffic with HTTPS; the following sub-sections 4.4.1 and 4.4.2 provide further details.

Table 4.6: HTTP Inbound Video Traffic by Month

	YouTube	DailyMotion	Vimeo	Hulu
December	1.93 TB	535.7 GB	69.3 GB	3.3 GB
January	1.89 TB	685.2 GB	108.4 GB	1.3 GB
February	1.74 TB	662.2 GB	119.4 GB	4.0 GB
March	2.08 TB	717.5 GB	79.9 GB	2.7 GB
April	1.51 TB	662.5 GB	62.9 GB	2.3 GB

We are not able to measure the viewers or sessions on campus for any video service (including NetFlix and Twitch). We encounter a couple of issues when trying to estimate the number of local viewers. The first issue is the use of Network Address Translation (NAT), which allows many machines to use a single IP address when accessing the Internet. NATs on campus mean that we are unable to assume that each local IP address is a single viewer or session. The second issue is that video connections may use parallel connections to access content, as we will describe in Section 4.4.3. The use of parallel connections by video services means that we are unable to simply count connections to a service as a single session or viewer.

4.4.1 HTTPS Traffic

When investigating HTTPS connections, we can observe very few application-level details. That is, for HTTPS connections, we cannot identify any request-response pairs, URIs, or headers. We could gain more insight if we used the same methods as Newton et al. [52]. The lack of headers (and therefore content-types) makes it difficult to measure all video traffic occurring over HTTPS. Thus we choose to investigate connections to known video services, and assume that they are transporting video. When measuring HTTPS traffic, we look in the Bro SSL logs for the connections to servers of interest, and then find those connections in the connection logs to obtain the number of bytes transferred.

Table 4.7: HTTPS Inbound Video Services by Month

	YouTube	Akamai	Vimeo	Yahoo Screen	Hulu	DailyMotion	Total HTTPS
December	36.2 TB	5.8 TB	32.1 GB	390.7 MB	152.2 MB	58.7 MB	73.6 TB
January	36.3 TB	6.0 TB	47.3 GB	341.7 MB	169.8 MB	93.7 MB	83.7 TB
February	45.5 TB	7.0 TB	67.6 GB	293.2 MB	392.4 MB	98.3 MB	101.8 TB
March	59.6 TB	8.5 TB	103.0 GB	294.4 MB	252.1 MB	96.3 MB	124.8 TB
April	52.4 TB	5.4 TB	69.9 GB	221.6 MB	203.3 MB	77.9 MB	107.3 TB

As Table 4.7 illustrates, YouTube sends much more traffic through HTTPS than through HTTP. The services listed in the table are expected to be sending video traffic YouTube and Akamai dominate monthly HTTPS volume, since they send multiple terabytes of traffic to campus. Vimeo's traffic is measured in gigabytes and the others are in megabytes – there are very few viewers for these services on campus. We will discuss YouTube traffic levels in more detail in sub-section 4.4.2. The other services send a small amount of video traffic over HTTPS. Since their levels are low, we will ignore them for later graphs.

4.4.2 YouTube Traffic Volume and Throughput

YouTube sends and receives a majority of its traffic through HTTPS. The unencrypted (HTTP) traffic to YouTube (or GoogleVideo) servers are embedded video links. We observed some HTTPS traffic being sent to YouTube. This corresponds to a user uploading a video;

see Table 4.8 for a monthly breakdown.

Table 4.8: YouTube Traffic by Month

	HTTP		HTTPS	
	Inbound	Outbound	Inbound	Outbound
December	1.93 TB	0.14 TB	36.22 TB	0.89 TB
January	1.89 TB	0.12 TB	36.31 TB	1.06 TB
February	1.79 TB	0.05 TB	45.47 TB	1.14 TB
March	2.08 TB	0.05 TB	59.63 TB	1.36 TB
April	1.51 TB	0.05 TB	52.43 TB	1.08 TB

Figure 4.1 shows total traffic via HTTP (yellow) and HTTPS (red) to and from YouTube and GoogleVideo servers for January 2015, with the inbound and outbound traffic split across the X-axis. We choose to plot the outbound traffic to YouTube since YouTube allows for the upload of user-generated content.

Figure 4.1 is used as an example of a typical month in terms of YouTube traffic. The combined (HTTP+HTTPS) outbound traffic to YouTube has an average peak daily rate of around 0.5 Gbps. Once in a while, we see bursts of outbound traffic (less than 0.1 Gbps); these are videos being uploaded.

4.4.3 Video Traffic

In Figures 4.2 through 4.6, we see the inbound network traffic from YouTube (red), NetFlix (green), and Twitch (blue), as well as the total HTTP+HTTPS traffic as a black line. The volumes of video traffic on campus follow the same diurnal patterns as the total traffic, since inbound video traffic is mostly human-driven. The sudden brief outages correspond to the times when Bro was reset on the server (to load new scripts). Twitch's traffic levels are hard to distinguish in these graphs as they are very low.

From Figures 4.2 through 4.6, we can see that the amount of traffic from the three largest video services is around half of the total HTTP+HTTPS traffic. Using these graphs, we can see a few different events, such as the network outages, winter and spring break, and a few sudden increases in incoming Web traffic. These sharp increases in inbound Web traffic (as

seen on February 11, 2015 in Figure 4.4) correspond to traffic from `windowsupdate.com`; i.e., security patches downloaded to Windows machines on campus.

Over our collection period, we observed 40.3 million connections that were involved with the transport of video content. That is, a response to a request in the connection had the content type set to "`Video/*`"; this excludes connections that transported "`Flash/*`" and "`Application/octet-stream`" content. When inspecting these video connections, we find that the average connection duration is 51.3 seconds, and the median value was 7 seconds. Figure 4.7a shows the cumulative distribution function (CDF) for durations for these connections. The Y-axis of a CDF graph shows probability and the X-axis shows what is being measured; in this case duration. There are two sharp increases in connection duration, one occurring at 1 second and the other at 30 seconds. We do not know the cause of the first increase; the connections each contact different hosts and request different video-types. The second increase may be associated with connections transporting ads, since 30 seconds is a common duration for ads (the same as TV).

Figure 4.7b shows the CDF for video connection sizes (in bytes) during the five-month observation period. In this case, we measure both inbound and outbound bytes per connection. The median inbound byte value is 484.25 KB, while outbound is 9.49 KB.

The characteristics of video connections appear strange at first glance, since they transmit little data and are very short. We believe that this behaviour is caused by DASH. The client may open a connection, or parallel connections, to request segments of the video, and then close the connection(s) when the client's buffer is full. This behavior would lead to a client using many small connections to stream a video, and this seems to be the behaviour we consistently observe in modern video streaming services.

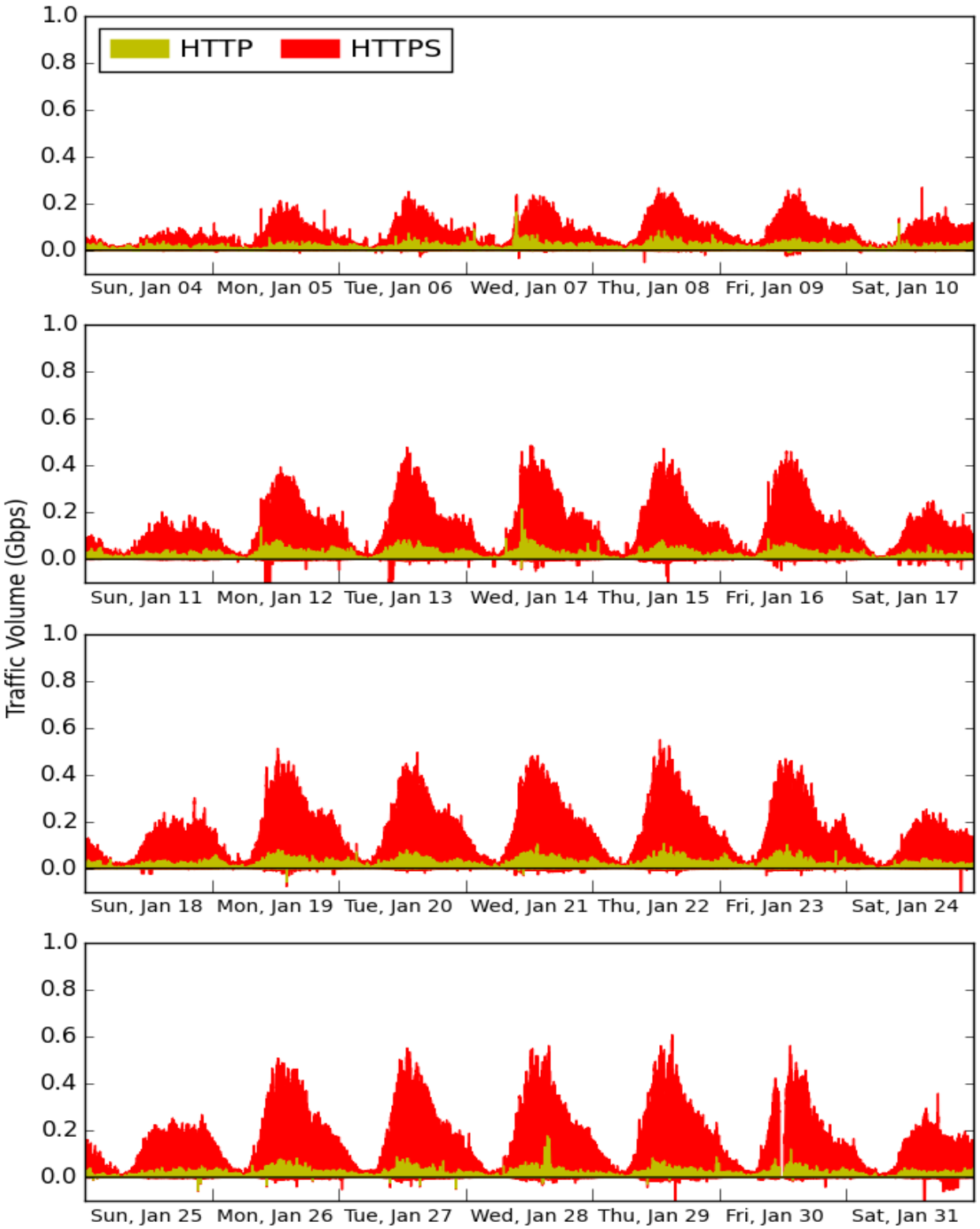


Figure 4.1: YouTube Traffic for January 2015

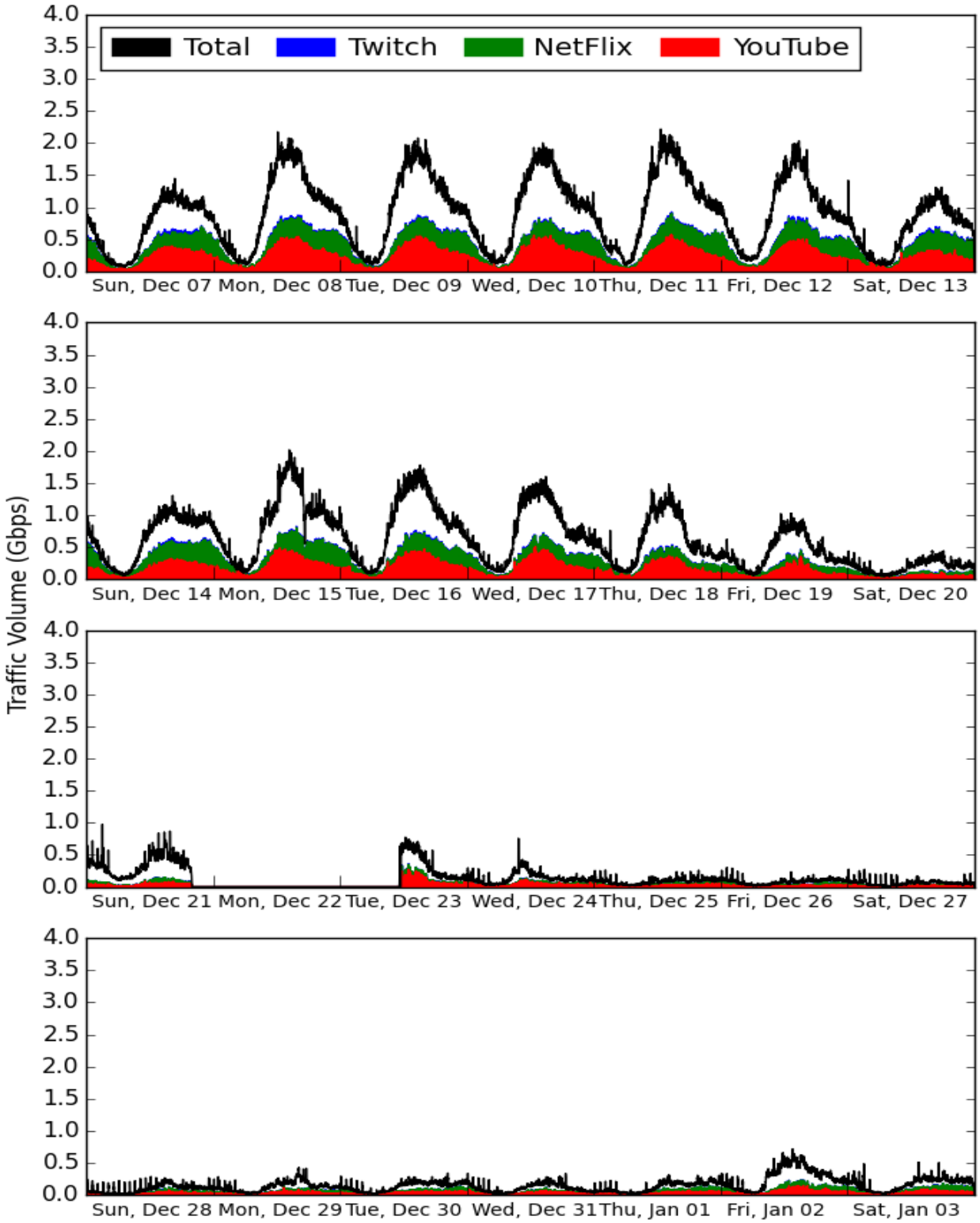


Figure 4.2: Video Traffic Comparison for December 2014

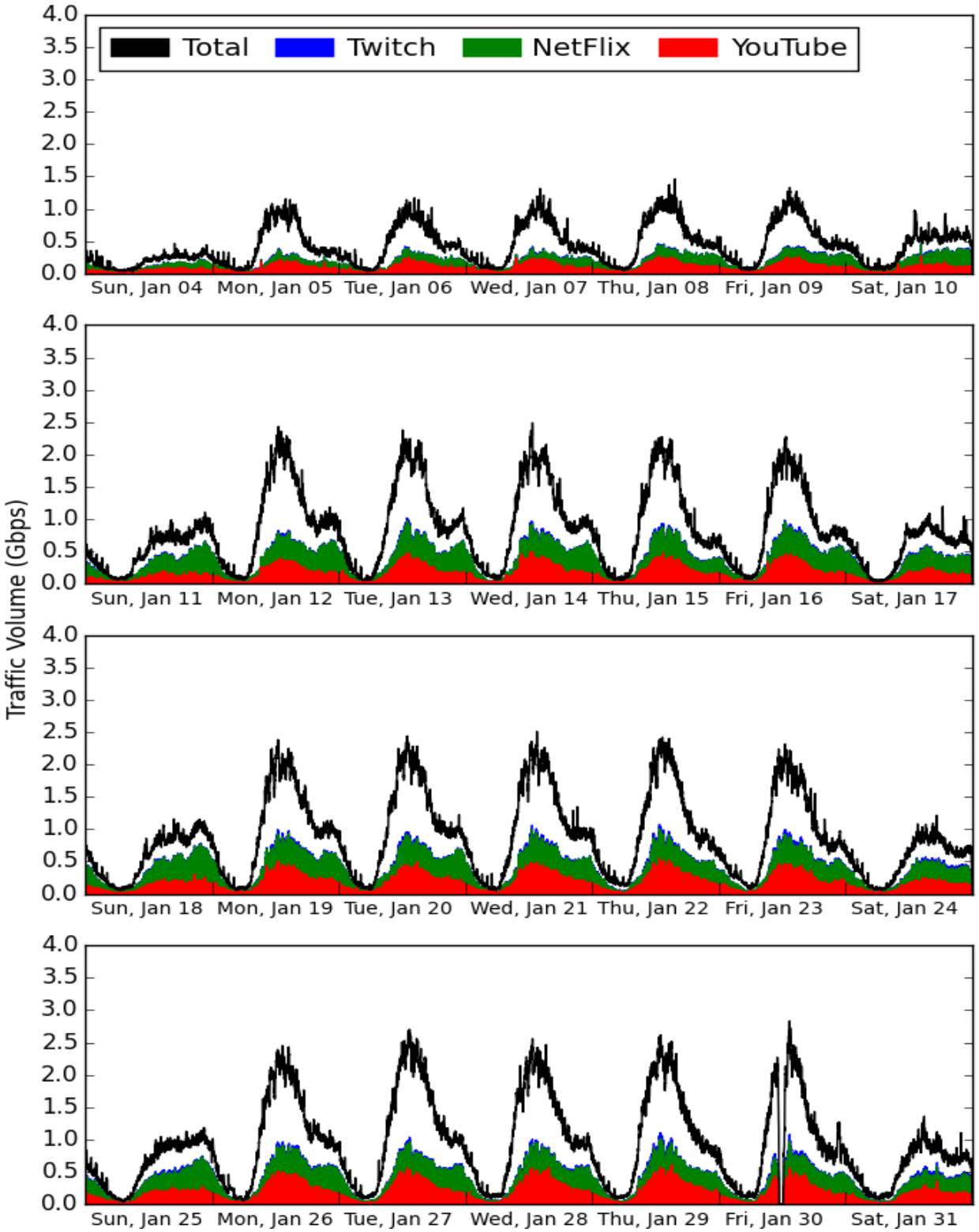


Figure 4.3: Video Traffic Comparison for January 2015

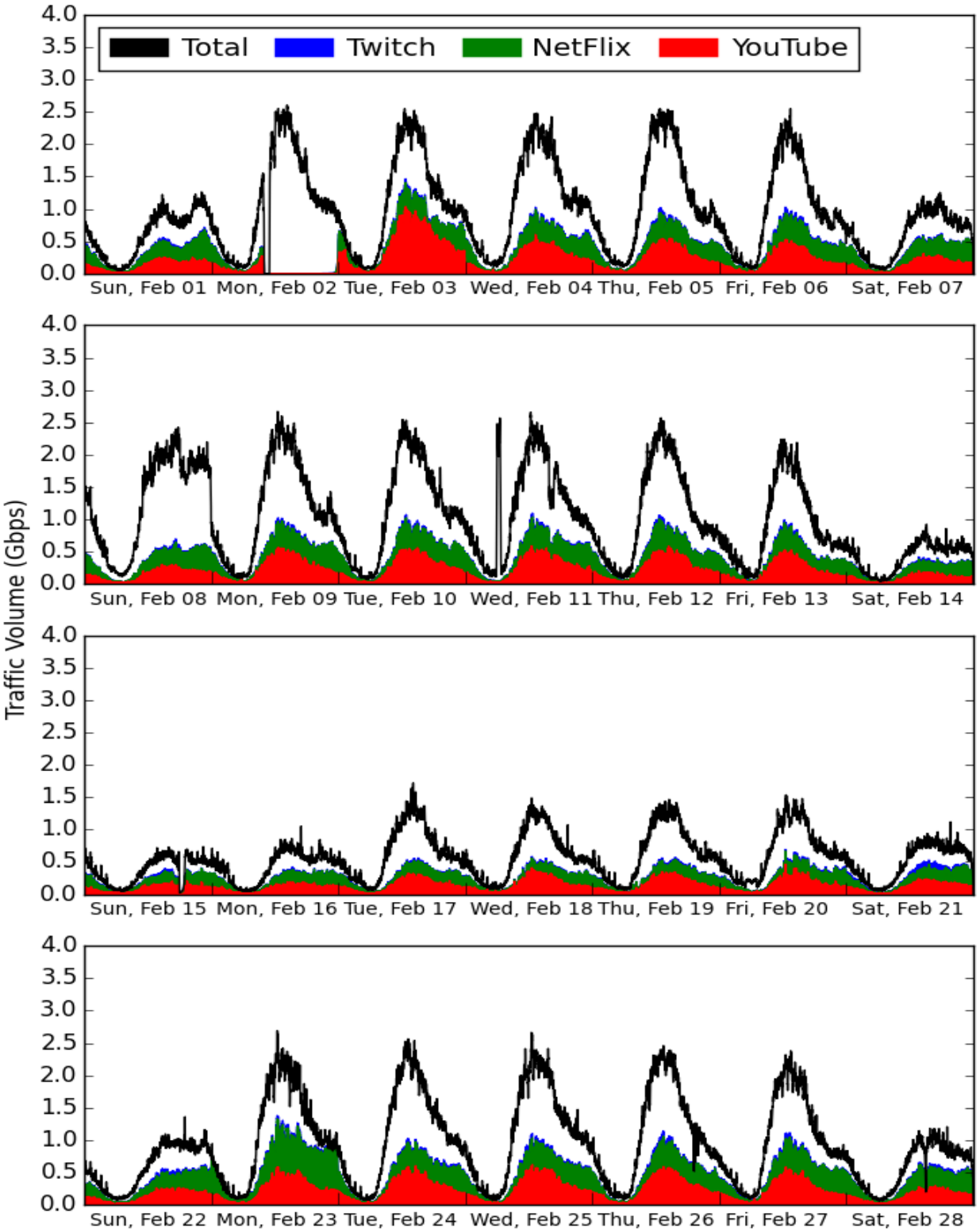


Figure 4.4: Video Traffic Comparison for February 2015

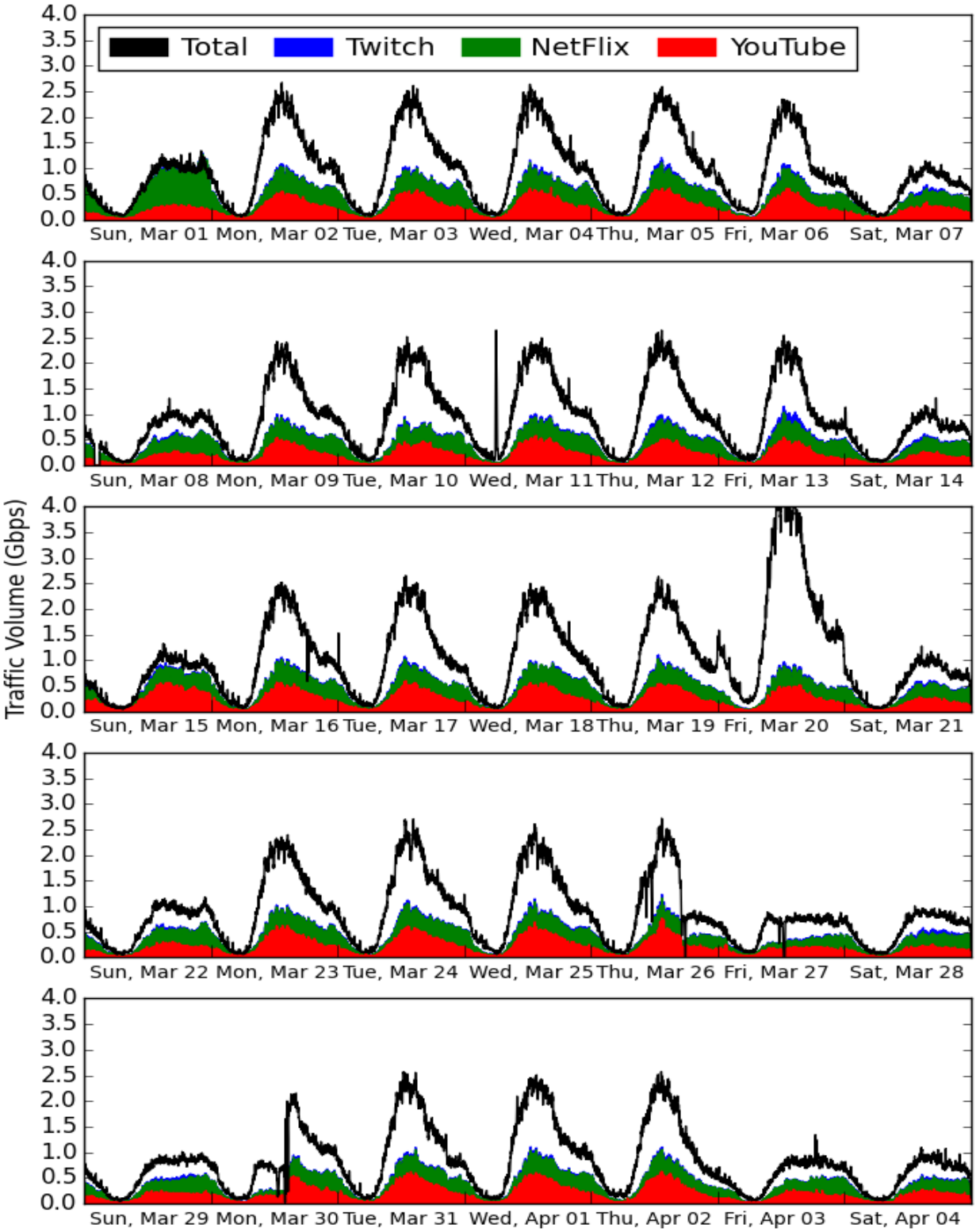


Figure 4.5: Video Traffic Comparison for March 2015

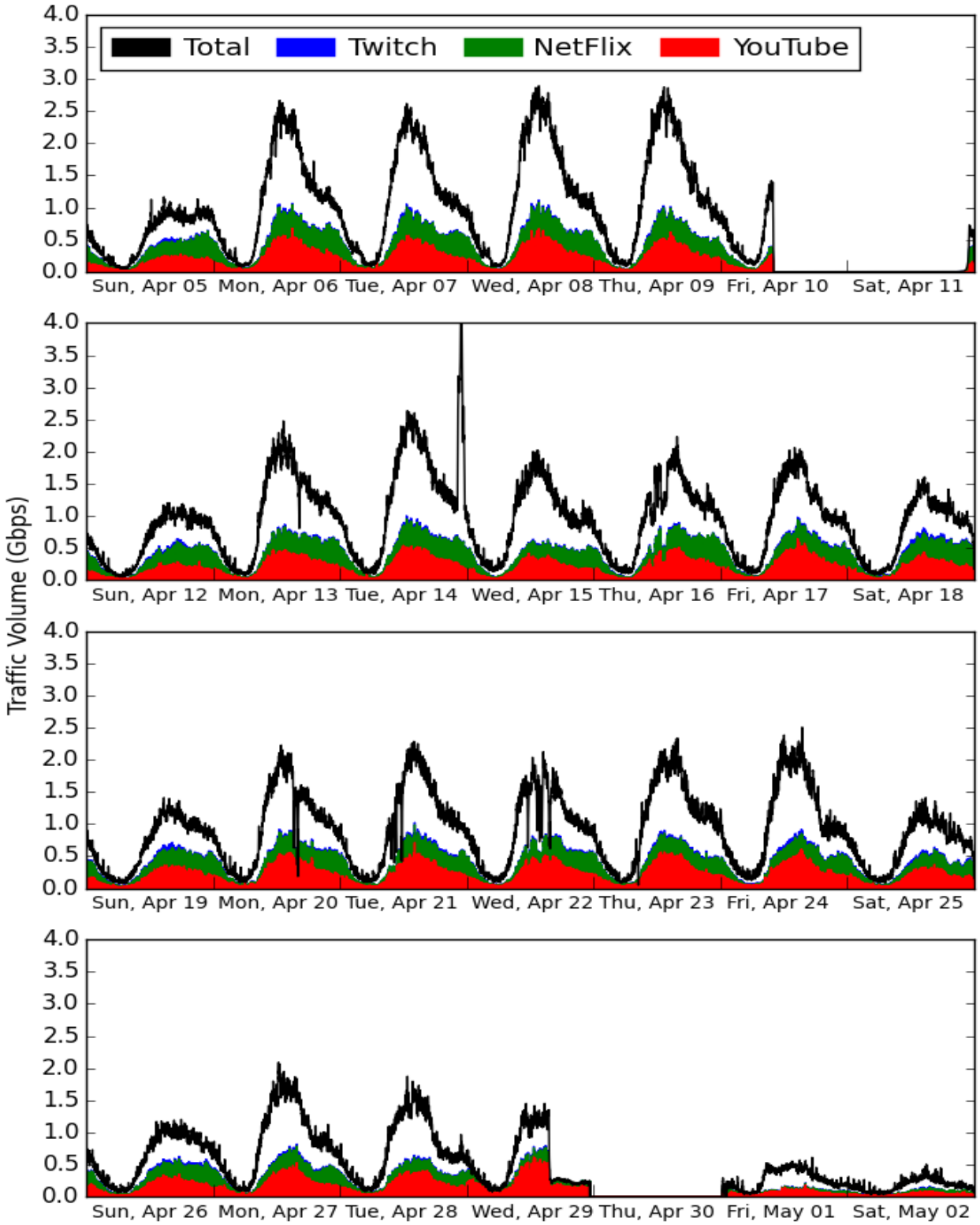
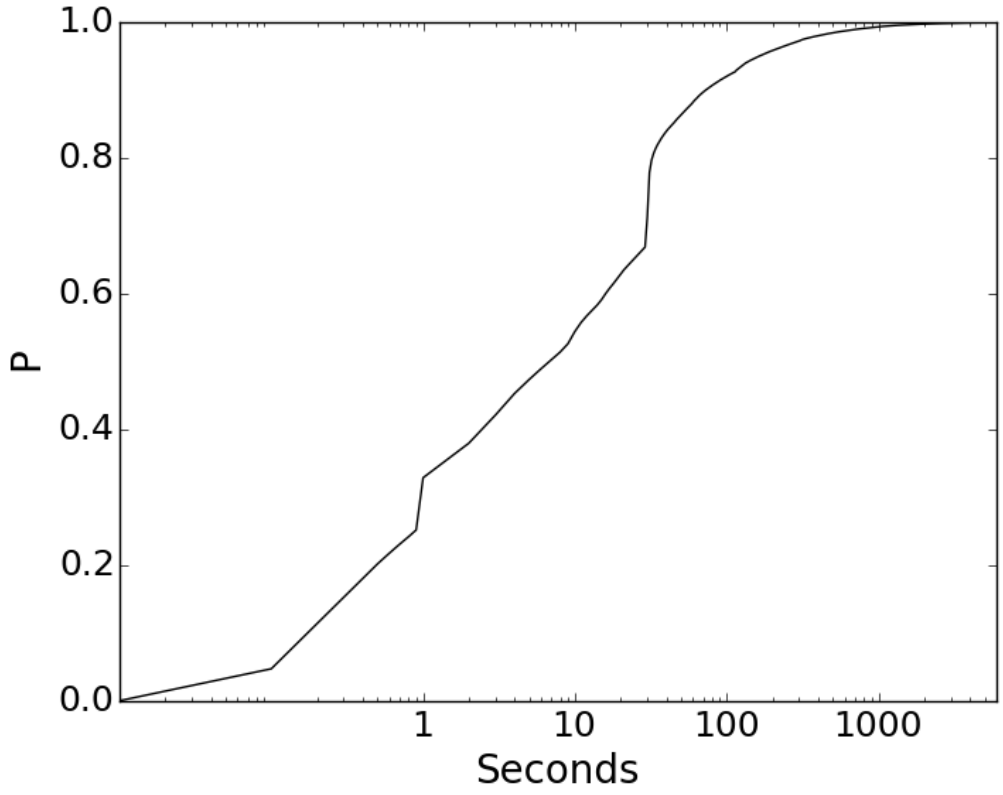
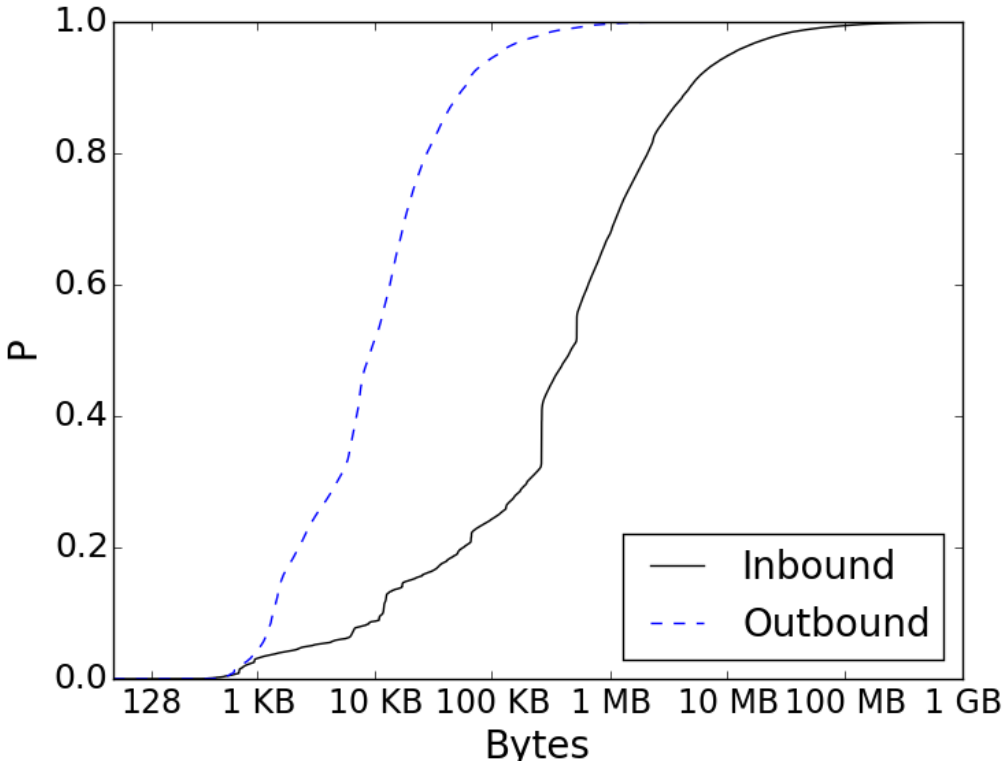


Figure 4.6: Video Traffic Comparison for April 2015



(a) Duration CDF



(b) Size CDF

Figure 4.7: December 2014 - April 2015 Video Connection Characteristics

4.5 Summary

In this chapter, we examined the visible video traffic levels on the University of Calgary's network. We determined the most popular types of video content, as well as the domains from which they originate. We investigated the levels of other content-types, such as Flash and Octet-streams. We find that most modern video services use a combination of their own servers as well as content distribution networks to provide content. We also gave a brief overview of YouTube traffic levels. Finally, we discuss general video traffic levels for the observation period, as well as characteristics for video connections. However, we are not able to measure the number of local viewers or sessions to video services.

In the next chapter, we examine the characteristics of NetFlix traffic during our observation period.

Chapter 5

NetFlix Analysis

NetFlix is a subscription-based video streaming service that is heavily used on campus[1]. Originally, NetFlix required the use of Microsoft's Silverlight plugin to stream content, but in October 2014 they switched to streaming HTML5 video over HTTP connections.

5.1 Desktop and Mobile Requests

Requests sent from a desktop Web interface to NetFlix differ from requests sent from mobile devices[2]. Mobile devices include Android phones and tablets as well as the Apple iPhones and iPads.

The requests from the different devices result in different request URLs. For instance, requests for (video) content from the NetFlix Web interface from a desktop look like:

`http://<IP>/range/?o=<o>...`

while requests from a mobile device's NetFlix App look like:

`http://<IP>/?o=<o>`

The 'range' section of a desktop request indicates a byte-range [68], as a workaround from the Silverlight implementation. These requests are made with the GET method and the response has a content type header of `Application/octet-stream`.

We observed 306 million requests to NetFlix. About 40% of all requests for NetFlix content over HTTP are made by mobile devices.

[1] Additional details about NetFlix can be found in the appendices. We describe the interface in Appendix C, associated IPs in Appendix D, and changes made to the request paths in Appendix E.

[2] We also assume that gaming console devices such as Playstation or Xbox make mobile requests.

The final important difference between mobile device usage and desktop usage of NetFlix is the collection of the referrer URI. In the case of a request for content by a desktop, the referrer URI is the request to `http://www.netflix.com/WiPlayer?...`. When a mobile device makes a request for content, the referrer is empty. Having the requests to the `/WiPlayer` path provides additional information. For example, these requests contain a parameter called the movieid, which we examine next.

5.2 Movie IDs

NetFlix uses a query string parameter named movieid to deliver content to the user. The movieid is a number that is sent with the requests to `/WiPlayer` (as part of a GET request). Each piece of content, movie, TV-show, or trailer has a unique movieid number. When sending a request to `/WiPlayer`, other parameters that are sent include trkid and tctx; these are probably used for user tracking. The response for this request has a content-type of `Text/html`. The movie content is requested by the player that loads from this page as described in the previous section.

When a TV series is chosen from the NetFlix menu, a general-purpose movieid is used. We will refer to this as ID_m (ID-main). This ID differs from episode-specific content, which we refer to as ID_e (ID-episode). A movie or trailer's movieid is ID_m, that is to say movies and trailers do not have any ID_e.

For a TV show, there seems to be no relationship between its ID_m and any of its ID_e values. For example, for the TV show *Breaking Bad*, the following IDs were observed:

- ID_m : 70143836
- ID_e Season 1 Episode 1 : 70196252
- ID_e Season 1 Episode 2 : 70196253

In the case of *Breaking Bad*, $ID_m << ID_e$, and ID_e numbers were allocated in sequential

blocks. For the case of *Breaking Bad*, when many seasons were uploaded at once, all the ID_e numbers are sequential, so episode 7 of season 1 (the last episode of season 1) has an ID_e of 70196258 and episode 1 of season 2 has an ID_e of 70192659. However, sequential numbers between seasons of a TV series are not guaranteed. In cases where NetFlix releases one season of a show at a time, the numbers between episodes can have gaps. For example, in *House of Cards*, season 1 episode 13 has an ID_e of 70248301, and season 2 episode 1 has an ID_e of 70293579. We have also seen cases where numbers in a single season do not behave sequentially.

If NetFlix auto-plays the next episode of a TV show, or if the user selects an episode to play from the episode list in the Web interface's player, the ID_e is added in the fragment section of the URI, i.e.,

`http://www.netflix.com/WiPlayer?movieid=<id1>...#episodeid=<id2>`

URI fragments are not transmitted over the network [7]. Instead, the video player reads the fragment and makes a request for that ID. ID_e numbers are not as common as ID_m numbers at a network level. We also are able to see movieid numbers for content that is not available in Canada; this is an indication that a user is using a third-party plugin (like Hola unblocker) to get around the geo-restrictions imposed by NetFlix.

5.3 Monthly Breakdown

5.3.1 Response Breakdown

We observed over 305 million request-response pairs for NetFlix on 14.3 million connections during our five-month collection period. Over 62.9% of responses had a code of 200 (OK), 29.9% had 206 (Partial Content), 0.87% had 202 (Accepted), 6.09% had no code, and all other response codes have $< 0.1\%$ of responses each. Out of the 305 million request-response pairs, 195 million pairs (63.9%) were for desktop video content (including notebooks), and

102 million (33.4%) were for mobile video content, and the remaining 8 million were for other non-video content, such as HTML, Javascript, images, etc.

Over the collection period, we observed 217.1 TB of traffic from NetFlix, 30% of inbound HTTP traffic or 8% of total traffic. The total volume of mobile (video) content was 54.01 TB, while desktop (video) content used 162.6 TB. Unsurprisingly, on desktop or mobile, no data was uploaded to NetFlix as part of requests for content. We observed over 15.1 million connections to NetFlix over HTTPS. These connections are mainly responsible for user authentication, payment, and access to the help-center. User ratings and reviews for content are sent over HTTP, through GET and POST requests, respectively. Over 357.4 GB of traffic was sent and 256.0 GB of traffic was received from HTTPS NetFlix servers over the collection period.

During the five-month collection period, we observed 35 different content-type headers on responses from NetFlix servers. The most transmitted content-type for responses by volume were: `Application/octet-stream` 216.7 TB (91% of responses), `Text/html` 328.3 GB (0.35%), `Video/mp4` 28.03 GB (0.01%), `Application/x-silverlight-app` 24.15 GB (0.01%), and `Application/javascript` 21.76 GB (0.04%). 6.46% of responses (with no volume transferred) had no content type.

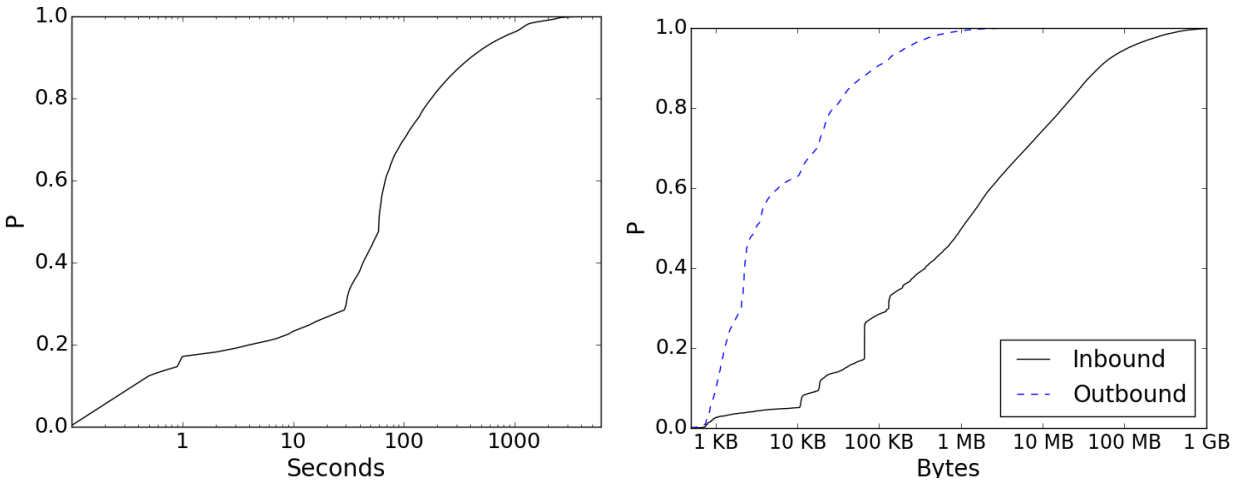
5.3.2 Breakdown of NetFlix video connections

Table 5.1 summarizes connections transporting video content from NetFlix. The average number of bytes NetFlix sends per connection is 26 MB, and the client sends around 370 KB. An important note about this count is that it includes the packet headers, thus we may assume that most client activity is TCP data acknowledgements. We can see that the average connection duration is just over two and a half minutes. This leads us to the conclusion that a client uses multiple connections to view content, since the content durations are greater than 2 minutes.

Figure 5.1a and 5.1b show the cumulative distribution function (CDF) plots for all Net-

Table 5.1: Monthly Connection Statistics

	Avg. Inbound Vol.	Avg. Outbound Vol.	Avg. Duration	Connections
December	27.72 MB	386.2 KB	166 sec	1,424,653
January	28.44 MB	384.6 KB	169 sec	2,067,609
February	26.47 MB	368.4 KB	169 sec	2,084,539
March	24.66 MB	367.2 KB	166 sec	2,794,287
April	24.30 MB	370.8 KB	165 sec	2,130,138



(a) Duration CDF

(b) Size CDF

Figure 5.1: NetFlix Connections from December 2014 - April 2015

Flix connections. The connection durations for NetFlix in Figure 5.1a show different behaviour than general video connections shown in Figure 4.7a. We find that the durations for most NetFlix connections last longer than general video connections. However, as NetFlix uses DASH [66] these connections are still small when compared to expected content duration. The outbound bytes in Figure 5.1b reflect the average bytes sent in a connection viewing content, as outlined in Table 5.1. The connections that send significantly more bytes are likely those involved with different user interactions, such as reviewing or rating movies. NetFlix utilizes parallel persistent connections to transport video. Requests on these separate connections may be interleaved; on mobile requests we typically see responses with a status of 206, while for desktop requests we see type 200 responses.

Response characteristics are summarized by month in Table 5.2. All requests made for

Table 5.2: NetFlix Responses - Monthly Summary

	Total		Desktop		
	Volume	Count	Avg. Size	Avg. Dur	Count
December	30.77 TB	44.4 million	851.3 KB	1.01 sec	24.4 million
January	44.41 TB	62.4 million	899.7 KB	1.21 sec	39.4 million
February	43.83 TB	61.6 million	895.2 KB	1.44 sec	38.4 million
March	54.29 TB	75.1 million	882.3 KB	1.80 sec	47.9 million
April	43.85 TB	61.9 million	845.7 KB	1.62 sec	39.6 million

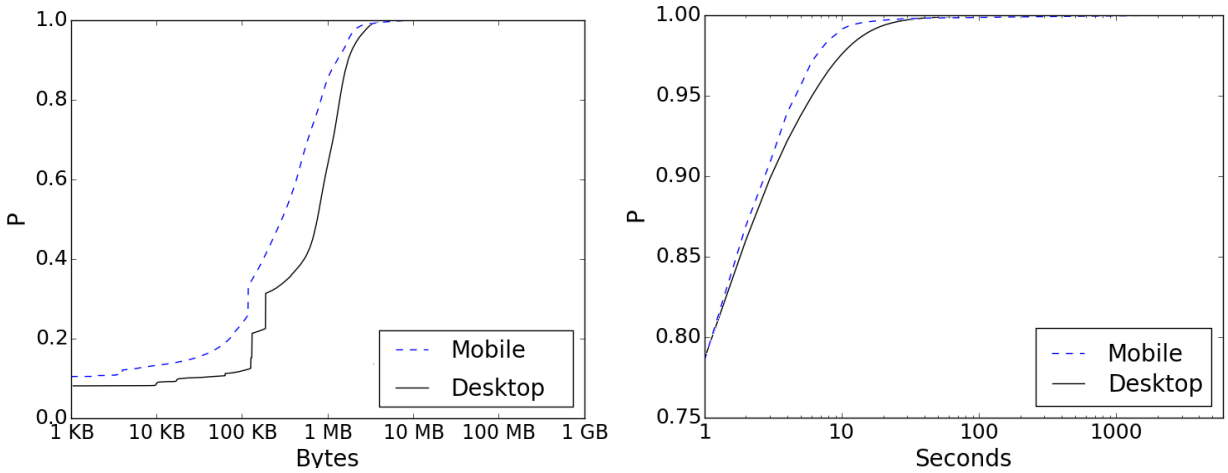
	Mobile		
	Avg. Size	Avg. Dur	Count
December	603.5 KB	1.83 sec	13.6 million
January	578.4 KB	1.64 sec	21.2 million
February	550.7 KB	1.65 sec	21.4 million
March	574.8 KB	1.86 sec	25.0 million
April	525.0 KB	1.66 sec	20.6 million

video content (summarized in the table) used the GET method, with a body length and duration of zero. This table shows that there was a 10 TB increase in NetFlix traffic in March; this may be due to March containing no breaks or exams when students were away from campus for an extended period.

Figures 5.2a and 5.2b show the response size and duration CDFs for desktop and mobile requests. Figure 5.2a shows that the responses going to mobile devices are slightly smaller than those for desktop devices. This may be due to mobile devices using only wireless connections to connect to the local network. Wireless connections tend to have lower throughput levels (when compared to physical options available to desktop devices). Figure 5.2b shows the response duration for desktop and mobile requests for December-April. We see that responses going to mobile device are slightly longer, once again due to mobile's wireless nature.

5.3.3 NetFlix Usage Patterns

Figures 5.3 - 5.7 shows the NetFlix traffic over our collection period. There are strong diurnal patterns in the NetFlix traffic. The low period occurs from 2:00-10:00, and the heavy period



(a) Response Size CDF

(b) Response Duration CDF

Figure 5.2: NetFlix Response Characteristics December 2014 - April 2015

is from 12:00-24:00. We can see a slight difference when examining weekday traffic versus weekend traffic, although the University calendar has a greater influence on the volumes. Weekday traffic often has two peak activity periods during the day. These peaks occur in the afternoon around 12:00-14:00, and late in the evening around 22:00-24:00. Weekend activity only shows the second period as a distinct peak. Behavior in residential networks may differ from what we observed as the first peak (in mid-afternoon) occurs during work hours; we do not believe any other characteristics we present would exhibit difference on a residential ISP.

Figure 5.3 shows the NetFlix traffic levels for December 2014. The traffic levels decrease during the second week since it was the final exam period for the University of Calgary. Traffic levels remained low for the last two weeks of the month for the holiday break, when many students left campus. In December, 23.35 TB of video content was sent to desktop devices and 7.36 TB was sent to mobile devices from NetFlix. The total connections to all NetFlix HTTP servers was 2,018,915. 70.6% of these connections were used to transport content.

NetFlix traffic levels for January 2015 are shown in Figure 5.4. The first week of January was "block week" for the University. Normal classes were not yet in session so the traffic

was lower than the rest of the month. On the morning of January 30th, the University had a network outage that interrupted our observational capabilities for about an hour. For the month of January, 33.16 TB of video content went to desktop devices and 11.76 TB went to mobile devices. 72.6% of 2,847,620 connections were used to transport content.

Figure 5.5 shows the NetFlix traffic levels for February 2015. On February 2nd, NetFlix had a service outage[3] and Bro did not log properly. During the third week of February, the University had "Reading Week", thus traffic levels are lower. We are unable to find the cause for the higher traffic levels for February 23. The total traffic from NetFlix on both the 22nd and 23rd was 1.62 TB, while the 24th was 1.74 TB. We expect that this spike is due to an error with the script that creates the time-series data for plotting. There were 2,849,154 HTTP connections to NetFlix servers in February. 32.60 TB of video content was sent to desktop devices and 11.15 TB was sent to mobile devices from NetFlix. 73.2% of these connections were used to transport content.

Figure 5.6 shows the NetFlix traffic levels for March. March had no major interruptions. We are unable to find the cause for the higher traffic levels for March 1st; it appears to be similiar to the issue on February 23. In March, desktop devices received 40.48 TB of content and mobile devices received 13.63 TB. The total connections to all NetFlix HTTP servers was 3,774,044. 74.0% of these connections were used to transport content. March's increase in traffic can be attributed to the fact that there was no break for students during the month.

Figure 5.7 shows the monthly traffic levels for April. On April 10-11, we see a failure with Bro, logs were not written from 10:00 on April 10 to 23:00 on the 11th. At approximately 15:00 on April 29th, our observational capabilities for the complete network ended. The traffic shown on the following days is not a complete view of network traffic. April had 33.07 TB of video content directed to desktop devices and 10.69 TB to mobile devices from NetFlix. The total number of connections to all NetFlix HTTP servers was 2,789,906. 76.4% of these connections were used to transport content.

[3] `https://gigaom.com/2015/02/03/netflix-not-working-outage/`

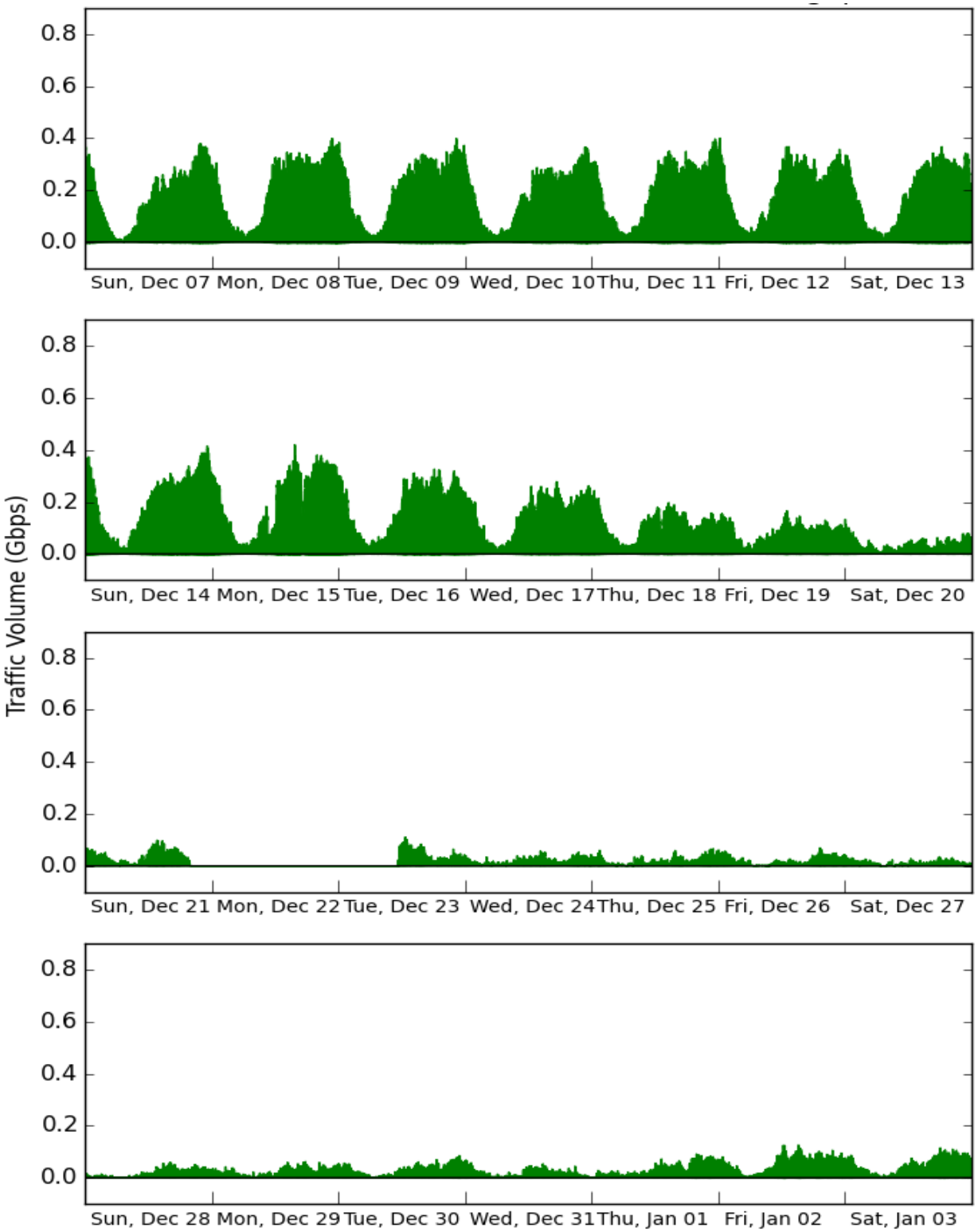


Figure 5.3: December 2014 NetFlix Traffic

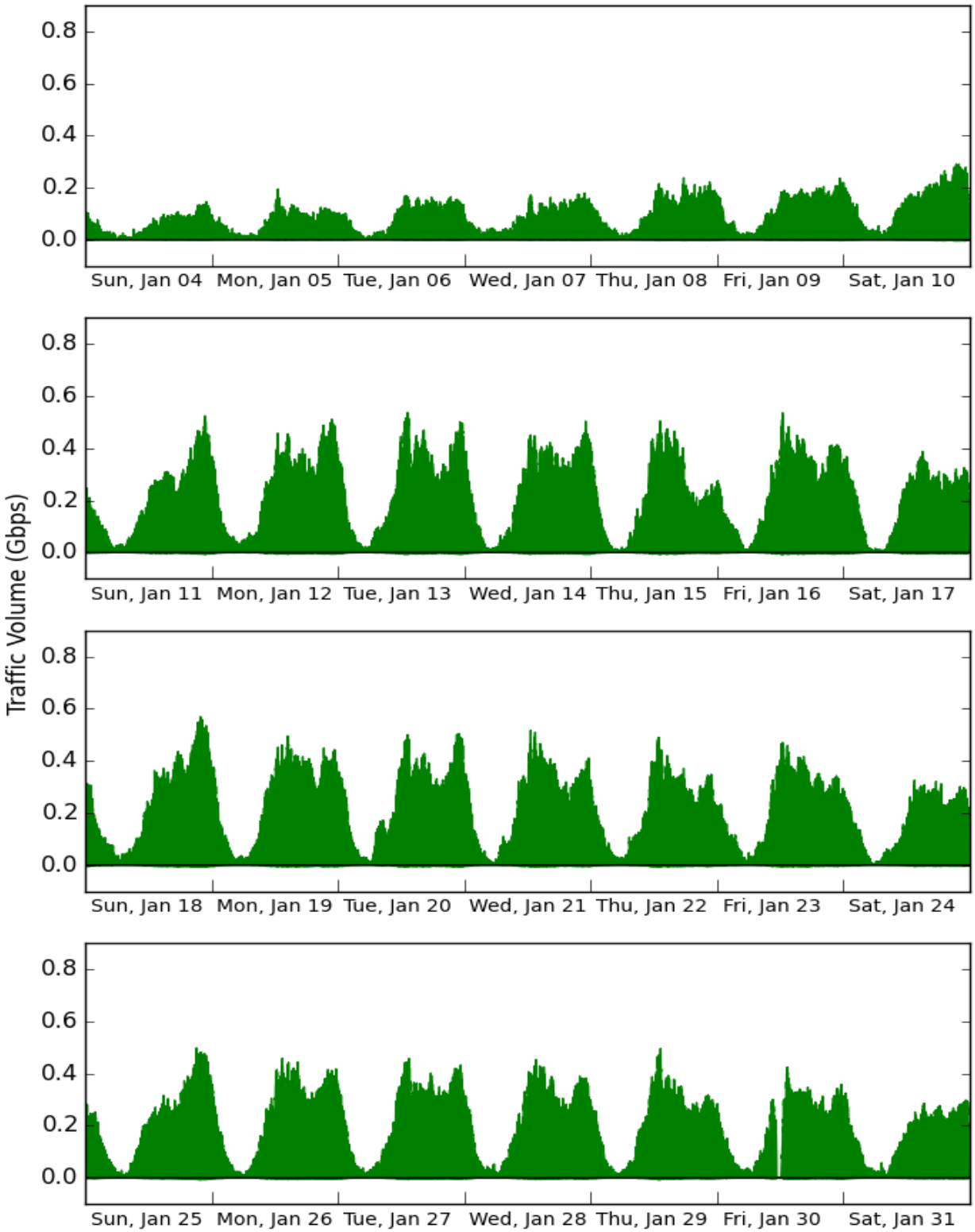


Figure 5.4: January 2015 NetFlix Traffic

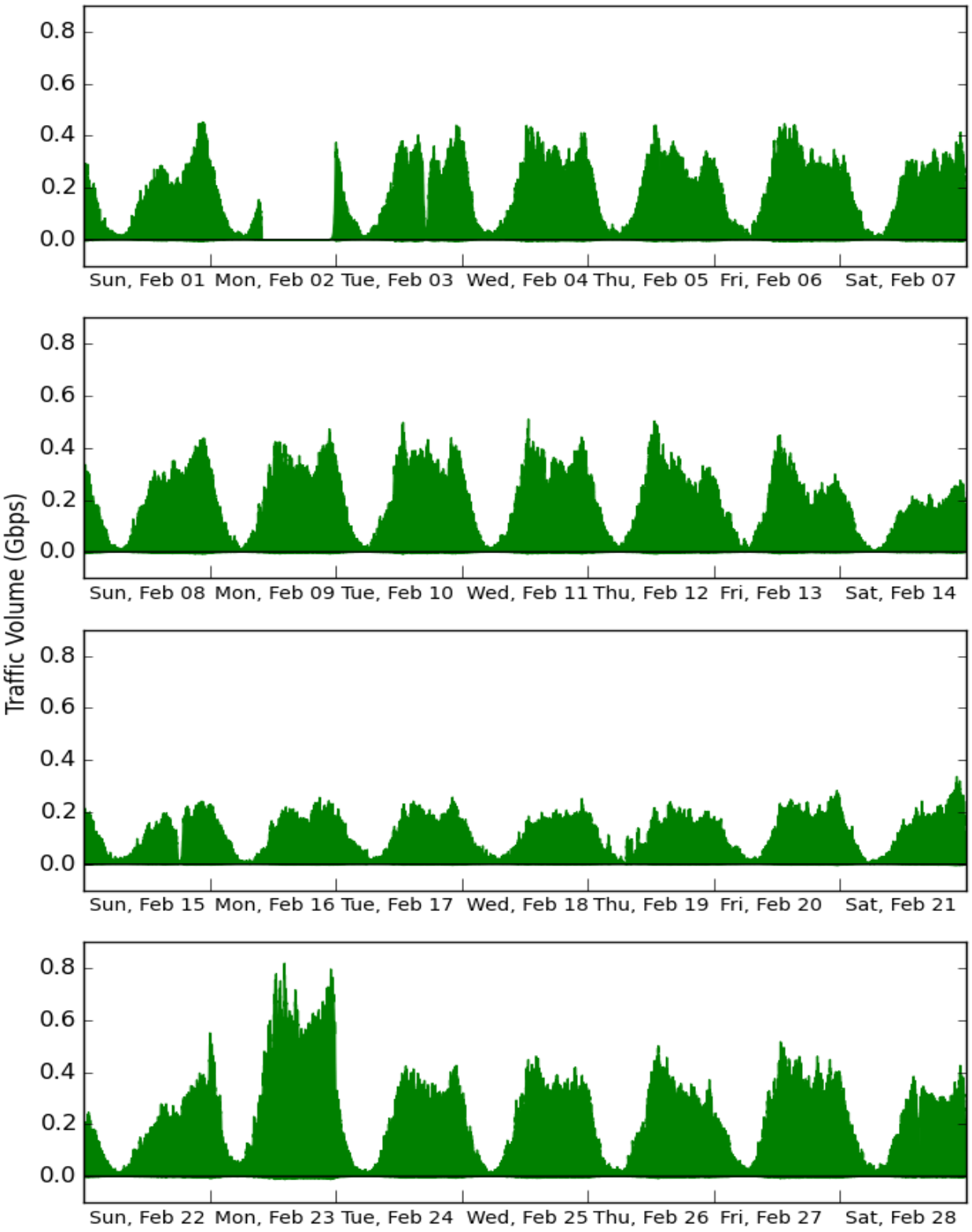


Figure 5.5: February 2015 NetFlix Traffic

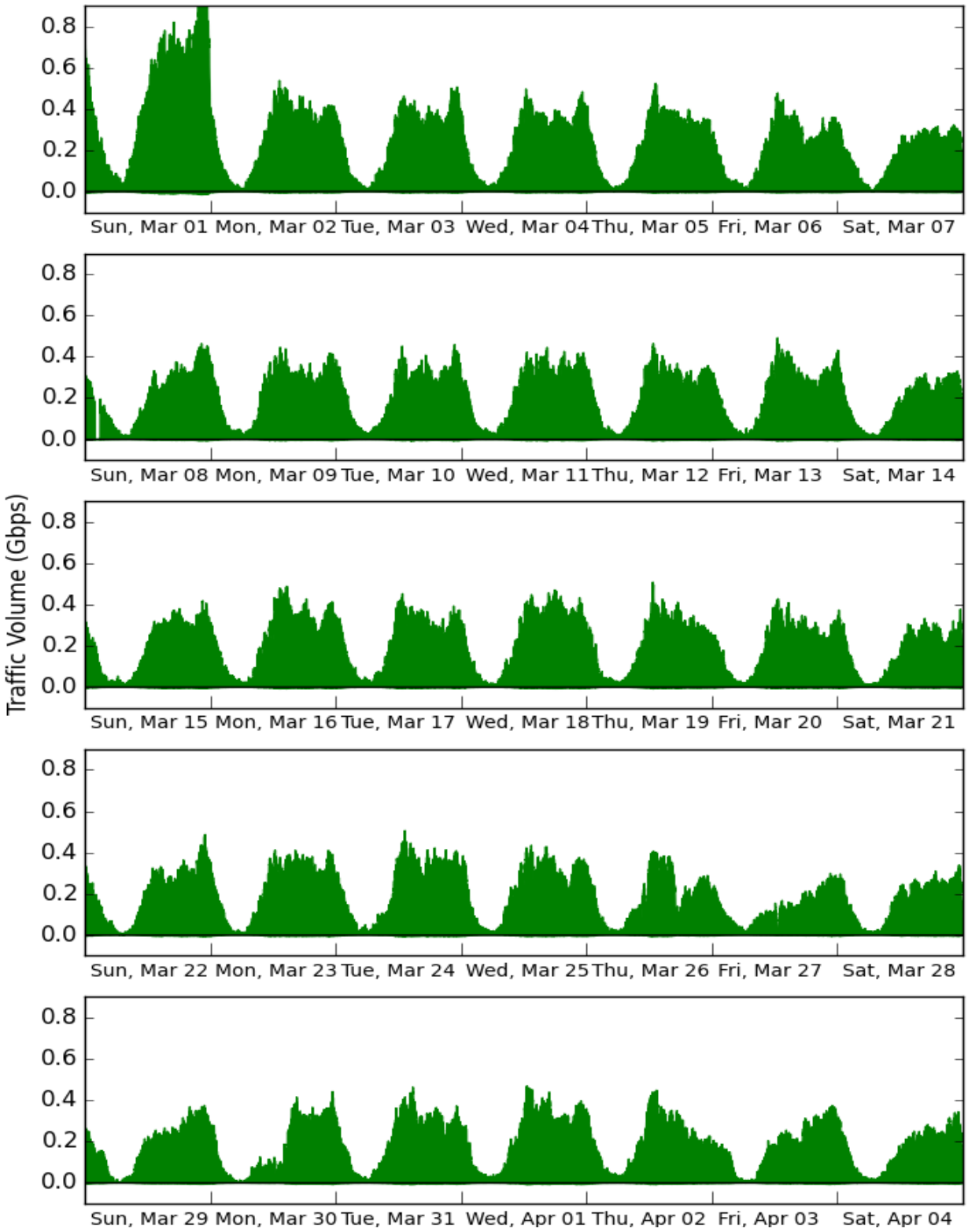


Figure 5.6: March 2015 NetFlix Traffic

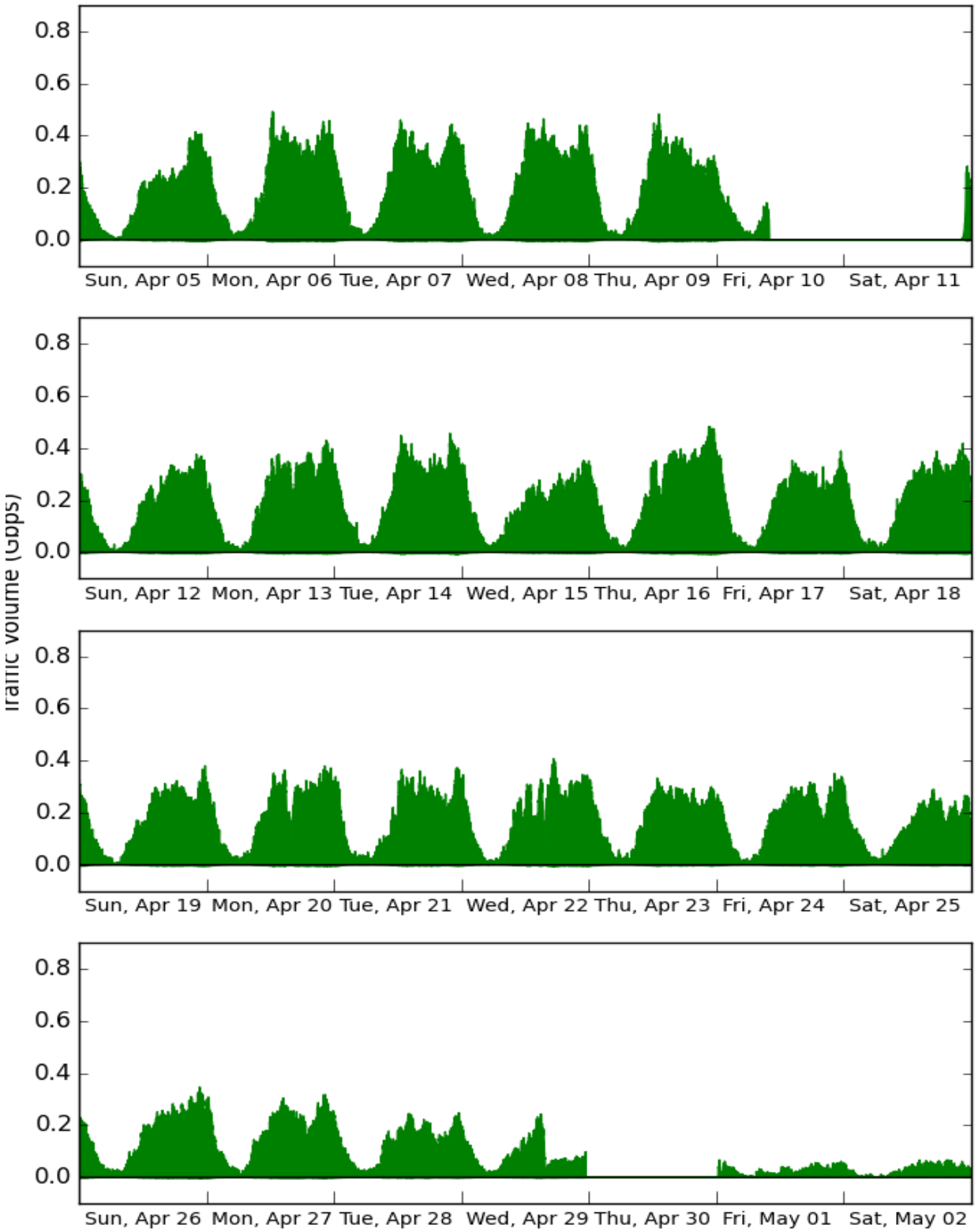


Figure 5.7: April 2015 NetFlix Traffic

5.3.4 Popular movieids

We can measure incoming octet-stream bytes from the desktop Web interface and map these to a movieid; mobile content is excluded since the movieid information is not available in the Bro logs. During the observation period, we observed 16,501 unique movieids sent to NetFlix, totalling 130.4 TB of transferred content, 60.06% of the total NetFlix traffic. We see less traffic with movieids (130.4 TB) than total desktop content (162.6 TB), since not every desktop request has a referrer field. Thus, we are unable to associate 82.2 TB of content (39.05% of total NetFlix traffic) with movieids.

We map movieids to titles by scraping a third-party Web site[4] with the main id, ID_m, of a movie or series. However, in the case of episode IDs, we were unable to find a way to automate a mapping between the ID and content title. We instead manually associated the episode IDs to titles using NetFlix's catalogue[5].

Over 50% of requested volume was associated with 25 different titles (2,801 movieids). The 25 most popular titles are shown with overall rank and volume, as well as monthly ranks in Table 5.3. Dashes in a column of the table indicate that the particular content had not yet been added to NetFlix's catalogue. When a TV show is listed, we include all bytes sent with the main ID, ID_m, as well as any bytes sent with an episode ID, ID_e, for that series. From this list, 24 of the titles are TV shows, and the lone movie, *Pitch Perfect*, sent just over 500 GB during our observation period. An explanation for the prevalence of TV shows is that a full season for a TV show is much longer than a single movie[6], and thus will transfer more bytes. It is also important to note that two titles on the list, *The Office* and *Parks and Recreation*, are not available in Canada. Users viewing this content were using some method to bypass NetFlix's geo-gating.

The popularity of transmitted movieids is shown in Figure 5.8. Both axis of this figure

[4] `www.allflicks.net`

[5] NetFlix does not provide an API to automate this.

[6] A show running 12 episodes at 21 minutes each has 252 minutes of content, while an average movie length is around 120 minutes.

are plotted with log scale. This figure shows that there is a long tail distribution for movieids. A long tail distribution is one where a few items account for a majority of occurrences. We can also see that there are many movieids that have transmitted very little volume, i.e., were relatively unpopular.

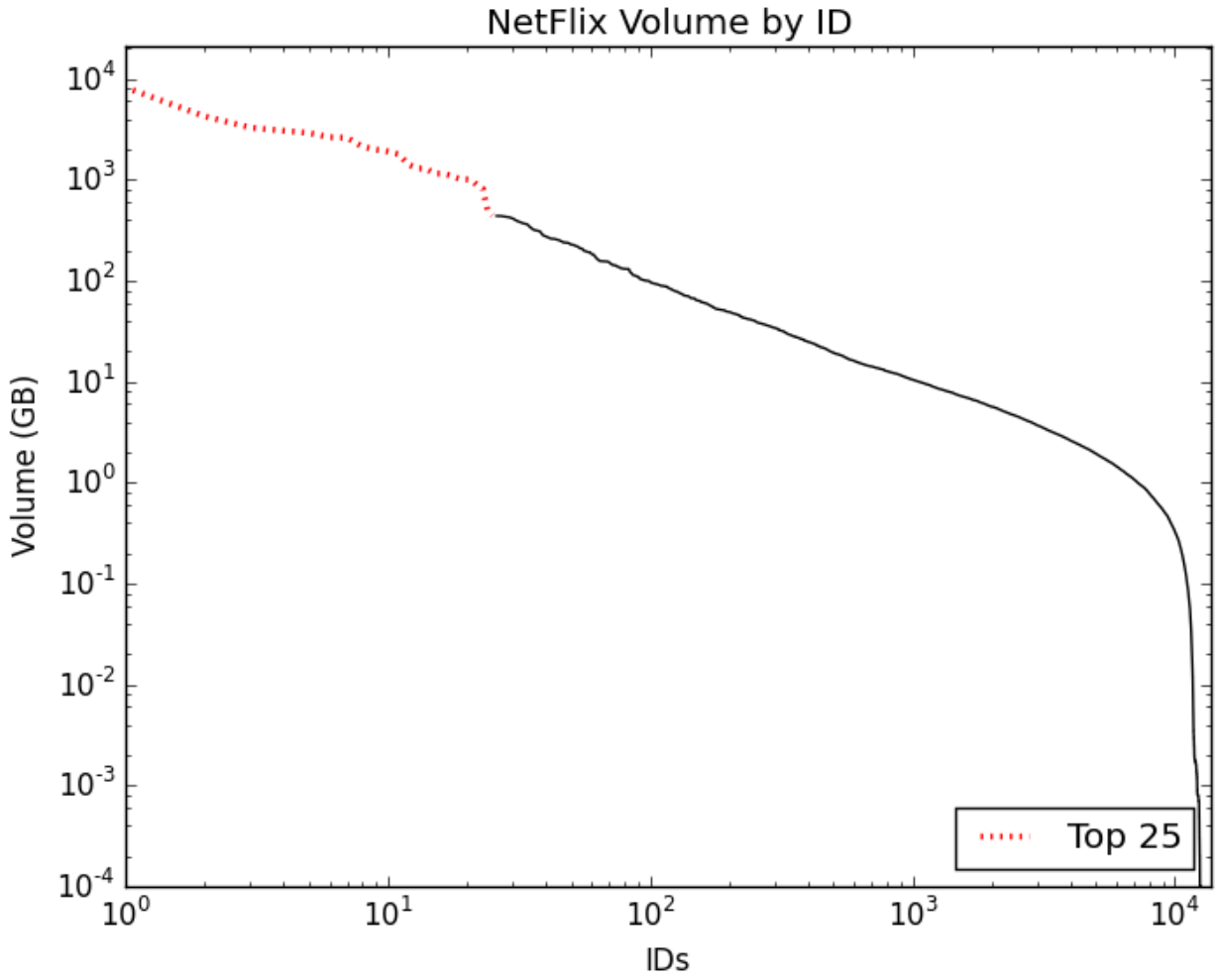


Figure 5.8: NetFlix ID Popularity

Using Table 5.3, we can see that popular content on NetFlix falls into one of two groups. The first group is content with long-term popularity. Examples of these are *Friends* and *Grey's Anatomy*; these series have a lot of content a viewer can watch and are very popular month to month. The second group is short-term content; this content is extremely popular for a month or two following its addition to the NetFlix catalogue. Examples of this type of

Table 5.3: NetFlix movieids by Rank on Campus

Title	Total Vol.	Dec	Jan	Feb	Mar	Apr
1. Friends	21.00 TB	-	1	1	1	1
2. Grey's Anatomy	8.20 TB	1	2	2	3	2
3. House of Cards	4.25 TB	20	16	3	2	9
4. Gilmore Girls	3.28 TB	2	4	9	10	5
5. Gossip Girl	3.05 TB	3	3	7	7	7
6. That 70's Show	2.90 TB	42	49	4	4	6
7. Suits	2.63 TB	6	5	10	5	10
8. The Mindy Project	2.61 TB	8	7	16	9	4
9. Supernatural	2.12 TB	5	10	6	12	11
10. House M.D.	1.99 TB	7	9	5	13	14
11. How I Met Your Mother	1.90 TB	4	12	13	11	13
12. The 100	1.79 TB	12	14	8	8	28
13. White Collar	1.41 TB	13	6	12	16	18
14. 90210	1.29 TB	17	41	15	18	8
15. The Vampire Diaries	1.29 TB	16	11	11	14	39
16. The Office	1.15 TB	11	20	19	15	15
17. Archer	1.15 TB	18	8	14	17	36
18. Daredevil	1.11 TB	-	-	-	-	3
19. Family Guy	1.06 TB	9	22	21	19	17
20. Dexter	1.01 TB	14	19	24	23	12
21. Unbreakable Kimmy Shmidt	1.00 TB	-	-	-	6	21
22. Parks and Recreation	980.44 GB	15	15	20	21	23
23. Orange is the new Black	870.31 GB	25	18	17	22	20
24. Friday Night Lights	815.43 GB	19	21	22	24	19
25. Pitch Perfect	500.56 GB	10	43	33	58	66

content include movies, such as *Pitch Perfect*, or TV shows that have a new season added on NetFlix, such as *House of Cards* or *Archer*.

When a single season for a popular show is added, viewers will consume the new content quickly. We can see this behaviour in the table with *House of Cards*; the series surged when the third season was added at the end of February (27th), and the surge lasted at least two months in this case, then started to wane. For *Unbreakable Kimmy Shmidt*, the show surged when it was added in March, but lost its popularity by April. We believe that viewers on NetFlix will "binge watch" newly added series or movies (short-term content), then return to watching older (long-term) shows.

One explanation for this is that a long-term show has a lot more content to watch. For example, *Friends* has 10 seasons of content available. The amount of content makes it more difficult for a viewer to fully consume in a short period of time. We present an example of this in greater detail in Section 5.4.

That 70's Show is another example of content exhibiting long-term popularity. Table 5.3 shows a jump from rank 49 to 4 between January and February – this surge-like behaviour is easily explained. Viewers watching the series in December and January were doing so by watching from the American catalogue, since it was only added to the Canadian catalogue on February 12th. Once added to the Canadian catalogue a great number of users on campus were able to access it.

We investigate the top ten IDs by volume per month in Tables 5.4 through 5.8. The volumes listed in the table once again include volume transferred with the main IDs, ID_m, and all episode IDs, ID_e, associated with the series. Items appearing in bold in a table indicate either new content to NetFlix, or additional content added in the given month.

Table 5.4: Top 10 NetFlix movieids for December 2014

	Volume	Percent	Title
1	1.3 TB	7.51%	Grey's Anatomy (TV)
2	813.4 GB	4.70%	Gilmore Girls (TV)
3	548.2 GB	3.17%	Gossip Girl (TV)
4	528.4 GB	3.05%	How I Met Your Mother (TV)
5	407.1 GB	2.35%	Supernatural (TV)
6	385.2 GB	2.23%	Suits (TV)
7	358.2 GB	2.07%	House M.D. (TV)
8	296.5 GB	1.71%	The Mindy Project (TV)
9	284.9 GB	1.65%	Family Guy (TV)
10	275.4 GB	1.59%	**Pitch Perfect** (movie)
	Total: 17.3 TB		

Table 5.4 shows the top shows for December. One characteristic of note is that the data volumes are relatively low compared to other months. This is due to the extended holiday break. Referring back to Figure 5.3, we can see that the traffic levels decrease through the

examination period and return to normal by the second week of January. The only movie listed in the table, *Pitch Perfect*, was added to NetFlix's catalogue on December 1.

Table 5.5: Top 10 NetFlix movieids for January 2015

	Volume	Percent	Title
1	7.6 TB	28.46%	**Friends** (TV)
2	1.7 TB	6.37%	Grey's Anatomy (TV)
3	707.4 GB	2.65%	Gossip Girl (TV)
4	701.0 GB	2.63%	Gilmore Girls (TV)
5	524.0 GB	1.96%	Suits (TV)
6	391.9 GB	1.47%	White Collar (TV)
7	358.7 GB	1.34%	The Mindy Project (TV)
8	334.7 GB	1.25%	**Archer** (TV)
9	321.2 GB	1.20%	House M.D. (TV)
10	294.3 GB	1.10%	Supernatural (TV)
Total: 26.7 TB			

The largest change in Table 5.5 for January 2015 is the *Friends* TV series, which is the most viewed content. This trend persisted for the rest of the observation period. The complete series was added to NetFlix on January 2nd, 2015. *Archer* had a new season (6) added on January 7. The other new item on the list, *White Collar*, was added on December 4th, and was the 13th most viewed show in December with 233.4 GB transferred.

Two additional items, *Law & Order: Special Victims Unit* and *The Interview*, which are not in Table 5.3, were in the top 20 viewed for January, at positions 13 and 17, respectively. *Law & Order: Special Victims Unit* is a TV series that had a new season added in January. *The Interview* is a movie that was added in January.

Table 5.6 for February 2015 shows once again that several items on the list have recently been added to the NetFlix catalogue: *House of Cards* had the release of the third season on February 27, while *That 70's Show* was added to the Canadian catalogue of NetFlix on February 12th. *The 100* was ranked 12th in December with 272.0 GB and 14th in January with 233.9 GB.

The only other item to reach the top 20 that was not in Table 5.3 was *Spartacus*, at rank

Table 5.6: Top 10 NetFlix movieids for February 2015

	Volume	Percent	Title
1	5.5 TB	20.99%	Friends (TV)
2	1.8 TB	6.87%	Grey's Anatomy (TV)
3	810.2 GB	3.09%	**House of Cards** (TV)
4	630.6 GB	2.41%	**That 70's Show** (TV)
5	565.4 GB	2.16%	House M.D. (TV)
6	547.6 GB	2.09%	Supernatural (TV)
7	448.2 GB	1.71%	Gossip Girl (TV)
8	437.7 GB	1.67%	The 100 (TV)
9	428.7 GB	1.61%	Gilmore Girls (TV)
10	415.4 GB	1.59%	Suits (TV)

Total: 26.2 TB

18 with 201.8 GB. *Spartacus* was added to the catalogue on February 3rd.

Table 5.7: Top 10 NetFlix movieids for March 2015

	Volume	Percent	Title
1	5.1 TB	15.45%	Friends (TV)
2	2.5 TB	7.58%	House of Cards (TV)
3	1.8 TB	5.45%	Grey's Anatomy (TV)
4	1.4 TB	4.24%	That 70's Show (TV)
5	853.7 GB	2.59%	Suits (TV)
6	800.7 GB	2.43%	**Unbreakable Kimmy Schmidt** (TV)
7	732.3 GB	2.22%	Gossip Girl (TV)
8	677.0 GB	2.02%	The 100 (TV)
9	598.7 GB	1.81%	The Mindy Project (TV)
10	567.9 GB	1.72%	Gilmore Girls (TV)

Total: 33.0 TB

Table 5.7 shows the top titles for March 2015. There was one new item, *Unbreakable Kimmy Schmidt*, which was added on March 6th.

The only item not listed in Table 5.3 to make it in the top 20 viewed for March was *This Is 40*; this is a movie that was ranked 20th in March with 219.8 GB of volume.

Finally, Table 5.8 has the top IDs for April 2015. On this list, we see two new items: *Daredevil* is a NetFlix original show that premiered on April 10th. The other show, *90210* was added in September. It was ranked 17th in December (173.1 GB), 41st in January (49.6

Table 5.8: Top 10 NetFlix movieids for April 2015

	Volume	Percent	Title
1	2.8 TB	10.26%	Friends (TV)
2	1.6 TB	5.86%	Grey's Anatomy (TV)
3	1.1 TB	4.03%	**Daredevil** (TV)
4	1.1 TB	4.03%	The Mindy Project (TV)
6	766.5 GB	2.81%	Gilmore Girls (TV)
5	755.9 GB	2.77%	That 70's Show (TV)
7	617.1 GB	2.26%	Gossip Girl (TV)
8	588.8 GB	2.16%	90210 (TV)
9	558.8 GB	2.05%	House of Cards (TV)
10	455.5 GB	1.67%	Suits (TV)

Total: 27.3 TB

GB), 15th in February (253.6 GB), and 18th in March (225.8 GB).

The only item not listed in Table 5.3 to reach the monthly top 20 list was *Mad Men*, which was 16th with 288.2 GB; the 6th season was added on April 7th.

5.3.5 Caching

One insight from the non-uniform access patterns to content, as well as the short and long-term popularity, is that caching would work quite effectively for reducing NetFlix traffic on edge networks. The easiest way to do so is to cache content on the local network. Unfortunately, due to NetFlix's measures for licencing and DRM, we would not be able to operate our own cache. Instead, one option that a network operator could pursue is hosting a NetFlix CDN node on the network.

NetFlix does not provide us with any information on how much space is needed to store each file. In order to figure this out, we ran a packet capture tool on a local machine and watched various types of content on NetFlix. We found that older shows, such as *Friends* and *Grey's Anatomy*, use less space than new shows such as *Daredevil* and *How I Met Your Mother*. This is because older shows were not filmed at high resolution. These shows were chosen for capture since they are selections that contain 20 and 40+ minute episodes. Furthermore, we found that an animated show such as *Archer* transmitted a similar volume

as live-action shows.

Table 5.9: NetFlix File Sizes

Title	Episode Length	Volume Transferred	MB/minute
Friends	22 minutes	293.99 MB	13.36
Grey's Anatomy	42 minutes	549.79 MB	13.09
Average MB/minute: 13.23			
How I Met Your Mother	21 minutes	476.13 MB	22.67
Archer	21 minutes	477.14 MB	22.72
Daredevil	53 minutes	1.84 GB	22.34
Average MB/minute: 22.58			

The estimated value of 22.58 MB/minute works out to be 3.01 megabits/second, close to the 'high' buffering levels seen by Ito et al. [33]. We estimate that the top 25 items would take a total of 1,870 GB to cache, which would be quite cost effective to do. We plot the transmitted volume and caching space required in Figure 5.9.

The International Movies Database (IMDB)[7] lists the entire runtime of *Friends* at 5,280 minutes; using Table 5.9 we estimate that it would take 70 GB of storage for the entire series. The total traffic from this series was at least 21.0 TB[8], roughly 10% of the total NetFlix traffic (217.1 TB). Caching this series would save at least 20.93 TB or 9.64% of total NetFlix traffic traversing the campus backbone. Using the rate for high-resolution video, we estimate that *Grey's Anatomy* would take 120 GB to cache. Caching this series would have reduced the WAN volume by approximately 8.1 TB over our observation period. *House of Cards* would take 40 GB to cache and could have reduced transmitted volume by over 4 TB throughout our observation period. We can see this diminishing returns effect in Figure 5.9.

For the other IDs we have seen from NetFlix, we can provide a very rough estimation of caching space needed. To estimate the amount of space each ID would take, we use the average from the top 25 (2,801 IDs). This works out to 0.667 GB/ID; 1870/2801 = 0.667. Here we plot transmission per ID (in a solid black line), and our estimation of space needed

[7] `www.imdb.com`

[8] We could only map 60% of content requests to movieids.

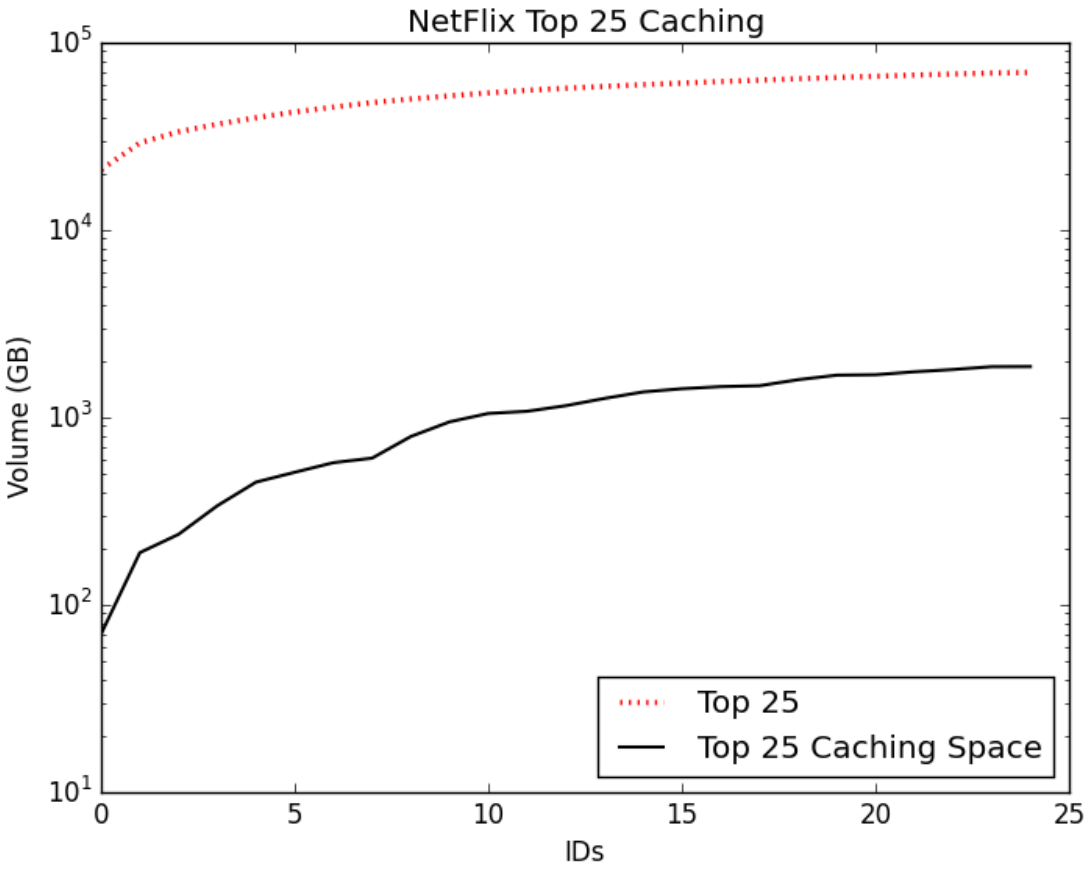


Figure 5.9: NetFlix Traffic and Caching Space for top 25 Shows/Movies

per ID (as a dashed blue line). We do not group by title as we did for Figure 5.9. The result of this estimation is visible in Figure 5.10.

We estimate that the total amount of space needed to cache all 16,501 ids is just over 11 TB. As we have stated previously, the top 25 pieces of content are associated with 2,801 IDs and account for over 50% of all NetFlix traffic. If we wanted to cache more content, the diminishing returns effect would have greater influence; that is, it would be less cost effective to cache more content. Caching content locally would greatly reduce traffic volume and provide better user experience.

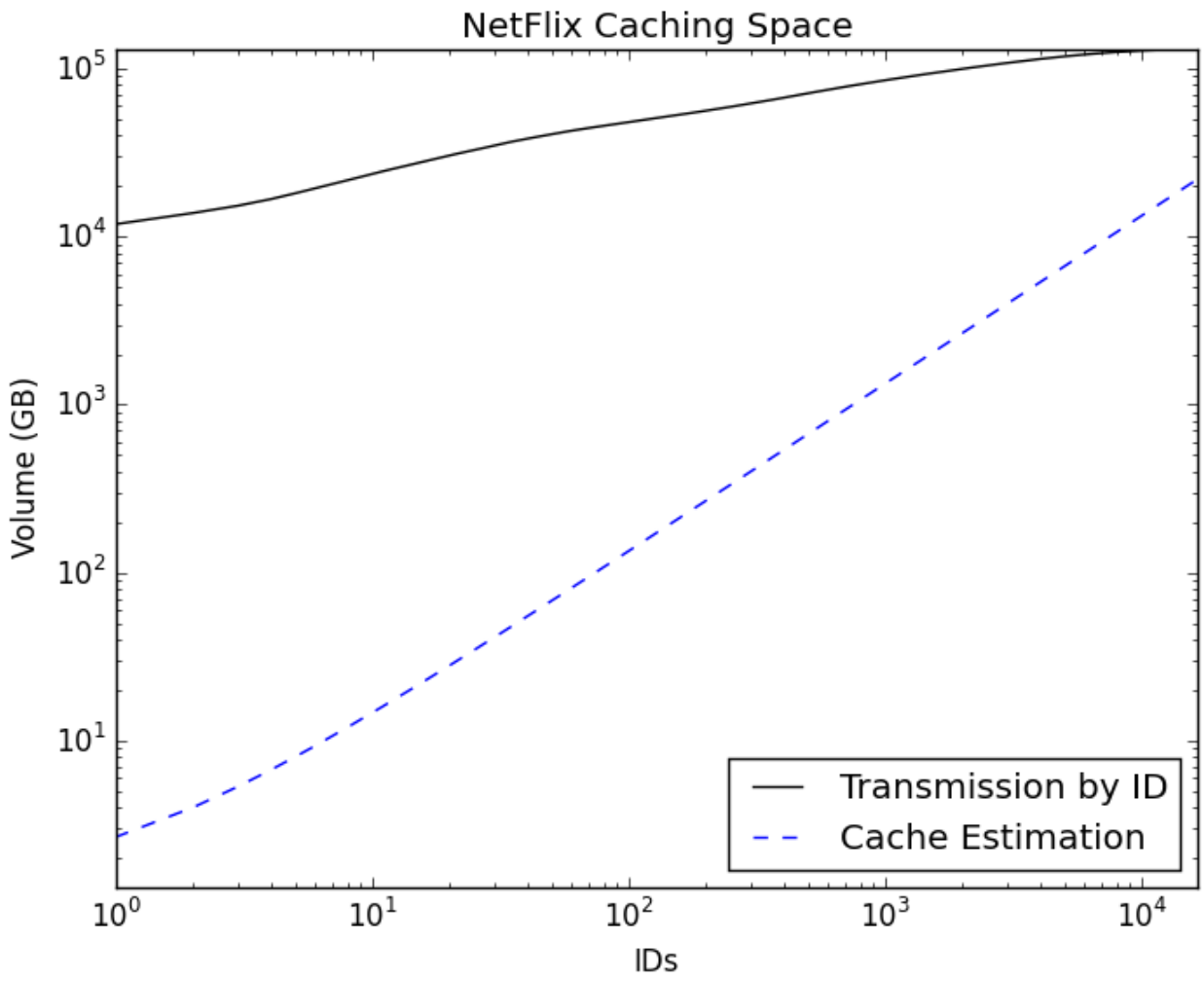


Figure 5.10: NetFlix Caching Space Estimation

5.4 Weekly Traffic

Figure 5.11 shows the traffic levels from NetFlix for the week of Sunday, April 12th – Saturday, April 18th. This week shows the difference between weekday peaks and the single weekend peak well. Outbound traffic is visible at this scale as well, for the request bytes, i.e., HTTP and network-level headers.

Table 5.10 shows the content summary statistics for the week in question. The table shows that about 75% of content from NetFlix is requested from desktop devices; this does not significantly differ from the overall desktop versus mobile content levels for the month. The daily numbers shown through the week are typical of a normal week from NetFlix.

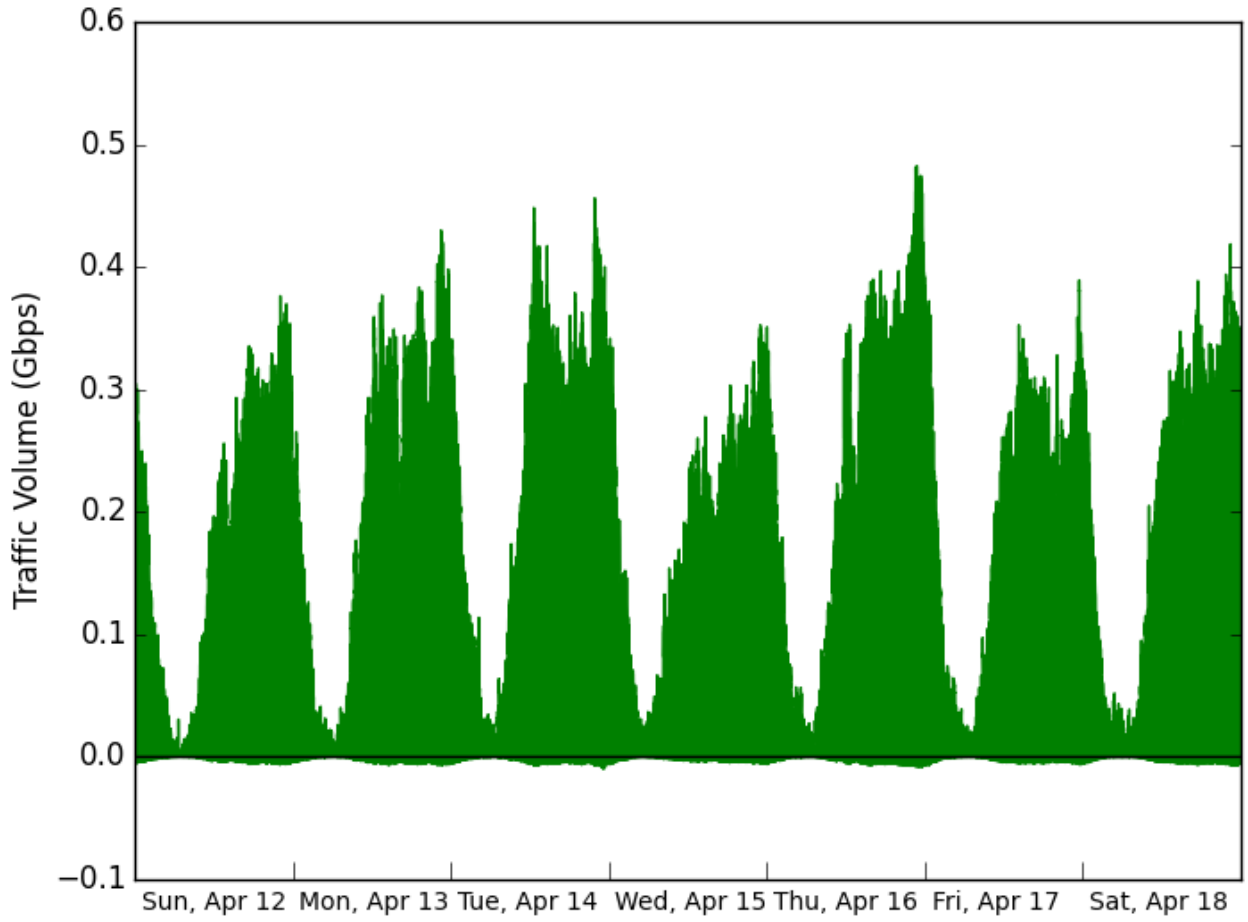


Figure 5.11: NetFlix Weekly Traffic April 12-18, 2015

Figure 5.12 shows the top titles through the week. The week of the 12th-18th is just after Daredevil was released. This explains its high popularity. The steady decline of bytes transferred for Daredevil throughout the week is also attributed to this fact. By the end of the week, Daredevil is transferring only half the content that it did at the start. This can be due to the fact that once the content was released, some viewers have either finished watching the entire season through the week, or that viewers watched an episode or two and lost interest.

Table 5.10: NetFlix Weekly Content Summary April 12-18, 2015

	Desktop Bytes	Desktop Responses	Mobile Volume	Mobile Responses
Sunday, April 12	1.244 TB	1,430,122	400.3 GB	756,499
Monday, April 13	1.371 TB	1,603,980	384.0 GB	762,610
Tuesday, April 14	1.407 TB	1,655,802	419.1 GB	858,386
Wednesday, April 15	1.110 TB	1,253,082	419.6 GB	824,446
Thursday, April 16	1.517 TB	1,866,650	435.4 GB	922,323
Friday, April 17	1.272 TB	1,504,304	404.4 GB	874,833
Saturday, April 18	1.432 TB	1,662,101	432.7 GB	820,183

5.5 Daily Traffic

In this section, we examine the NetFlix traffic for a day. We chose Tuesday, April 14th since it is a typical day in regards to NetFlix traffic.

On the 14th, the total number of connections to HTTP NetFlix servers was 120,399. The average bytes from NetFlix in a connection was 25.68 MB, with 400.9 KB sent to NetFlix. The average connection duration was 173.4 seconds.

We tracked a few individual NetFlix sessions (at a later date) on an end device and found that when watching a 22-minute episode, around 7-9 TCP connections are used, and an average of 430 HTTP requests are sent. When watching a 42-minute episode, 12-14 TCP connections are made, and 820 HTTP requests are sent.

We observed 94,212 connections (78.2% of total) making 1,655,802 requests for content from NetFlix. The average size of content responses was 890.8 KB for desktops and 512.0 KB for mobile devices. The average duration for these responses was 1.99 seconds (desktop), and 1.75 seconds (mobile).

The total bytes from NetFlix during the day was 1.830 TB, with 1.826 TB having a content-type of `Application/octet-stream`. 91.7% of the day's responses had the content-type header set to `Application/octet-stream`.

Figure 5.13 shows the traffic levels for NetFlix on Tuesday, April 14. The low area is between 2:00-11:00. In fact, between 1:00-4:00, we see a decline in volume that likely corresponds to viewers going to sleep. We can also see two individual peaks of activities

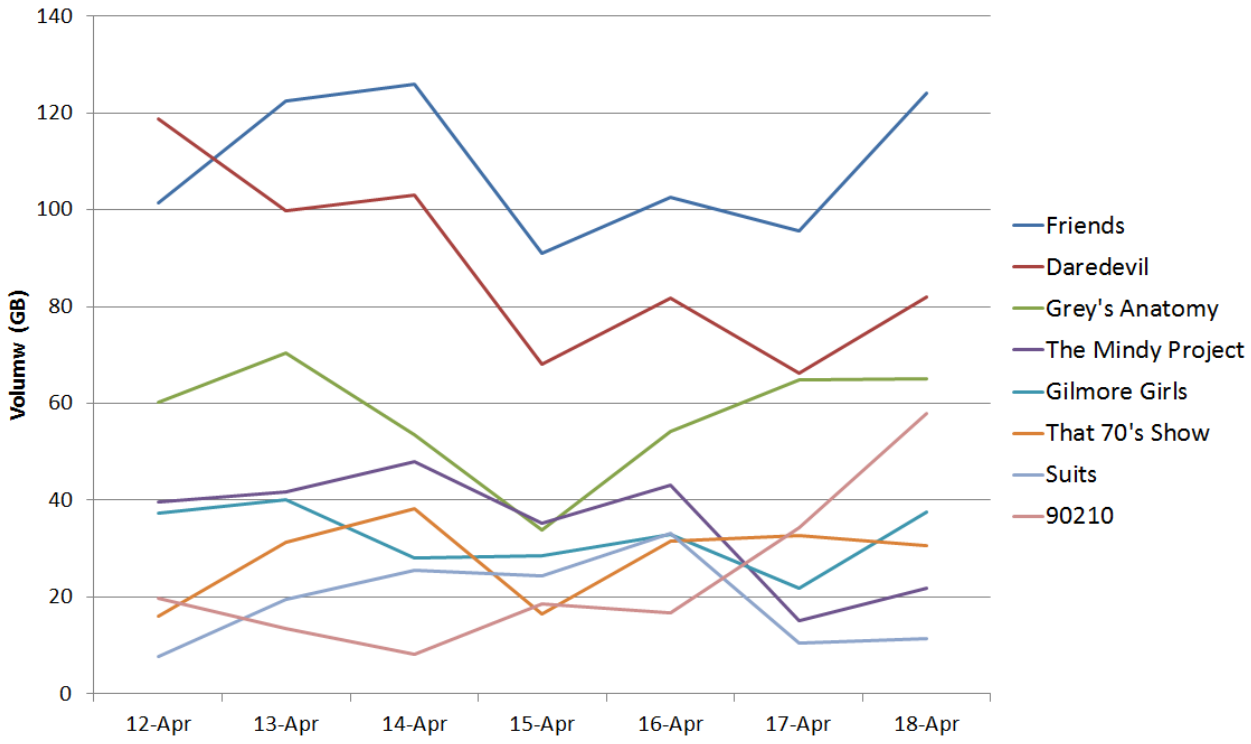


Figure 5.12: NetFlix: April 12-18, 2015, Top Content Trends

during the day: one in the afternoon, and one at night.

5.6 Summary

In this chapter, we investigated NetFlix traffic patterns at the University of Calgary. We expect that residential networks may show different daily access patterns than what we saw on campus as our peaks occurred during work hours. We described the basic requests used to retrieve content from the service. We found that requests from desktop and mobile devices differed, and measured both of them. We were able to measure and characterize what content (desktop) viewers watched. Furthermore, we presented our estimation of the space needed and benefits of caching content or hosing a NetFlix CDN node locally.

We presented a monthly breakdown of traffic for all five months of our observation period where we measured the amount of traffic, characteristics of the connections, as well as the HTML request-response pairs. We finished by summarizing the NetFlix traffic for a specific

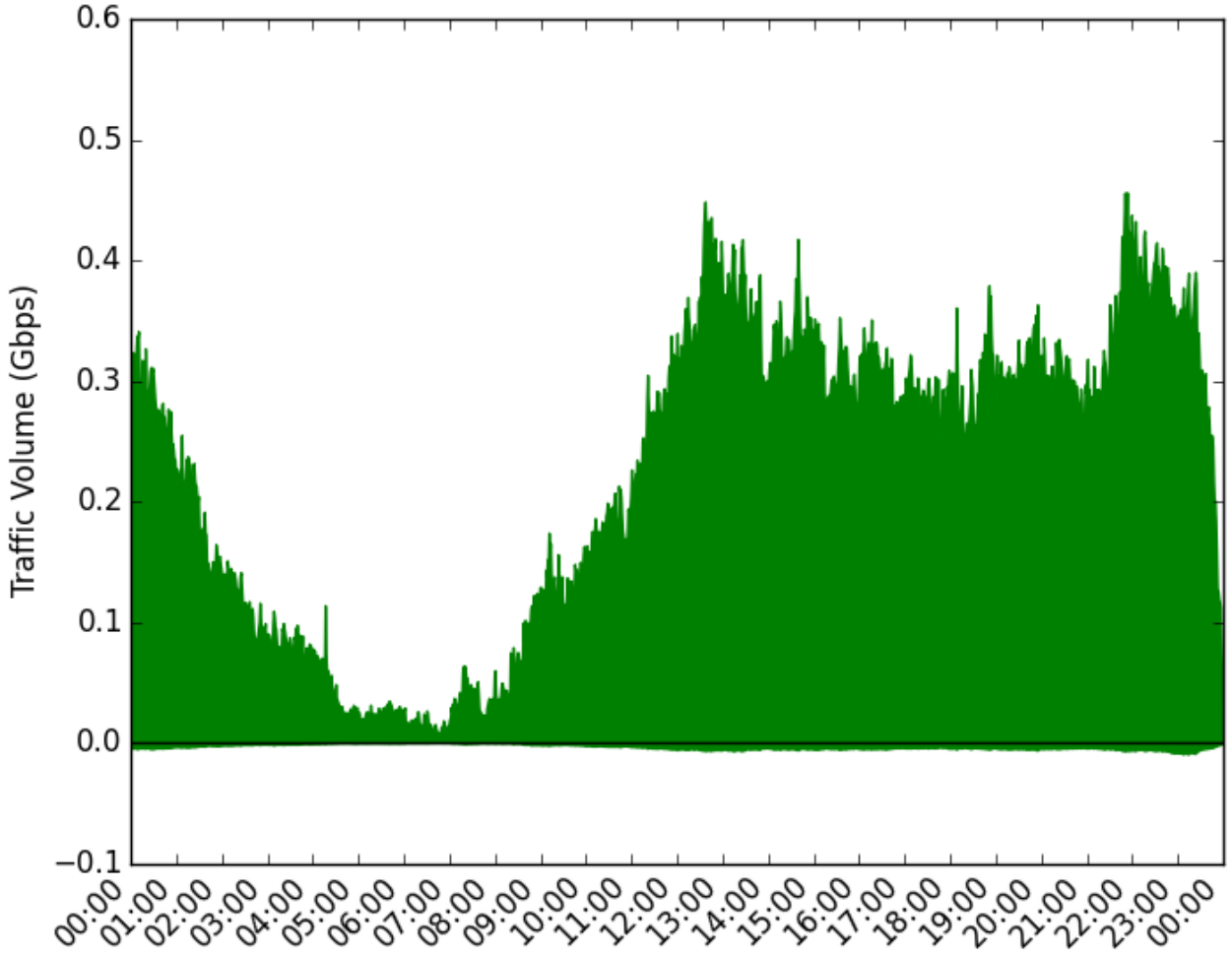


Figure 5.13: NetFlix Traffic Tuesday, April 14, 2015

week and day in the observation period.

In the next chapter, we present our characterization of Twitch traffic.

Chapter 6

Twitch Analysis

Twitch is a Web-based service that focuses on the live-streaming of non-sports games[1]. It primarily hosts video-game streams, although there are occasional card or board games featured as well. Twitch allows the streamer of a game to interact with viewers in (near) real-time with the use of a chat room associated with the stream. There is a small delay between the stream and real-time events, i.e., the stream shows events a few seconds after the streamer has encountered them.

There is no mandatory login when visiting `www.twitch.tv`, unlike the case with NetFlix. We will refer to Twitch users with two different terms for the rest of the chapter: a 'streamer' is a user who is creating content on Twitch, and a 'viewer' is a user who is viewing content on Twitch.

6.1 Live-streaming

As previously stated, we see video content served from HLS Twitch servers. For simplicity, we use the `twitch.tv` hosts instead of any other hosts for our examples (host names used by Twitch are described in Appendix G), since there does not seem to be any difference in requests made to them. Live-streamed content arrives from an HLS server that conforms to the following naming scheme[2]:

`video<i>.<Location><j>.hls.twitch.tv`

[1] Additional details about Twitch can be found in the appendices. Twitch partnership and subscriptions are summarized in Appendix F, the interface is described in Appedix G, and VOD measurements are presented in Appendix H.

[2] We have observed connections to Twitch servers after our observation period with the host names similar to `video-edge-83612c.sfo01.hls.ttvnw.net`, which does not conform to the previous schema.

In this scheme, i and j are each two-digit numbers (e.g., 01 or 12), and the location is a three letter code that corresponds to the server's geographical location (e.g., 'jfk' indicates the server is in the New York region).

Client requests made for live video content are HTTP GET requests for content following a specific path. The general request path scheme is as follows:

```
/hls<k>/<streamer>_<l>_<m>/<quality>/index-<n>-<h>.ts
```

where k is a number with no relation to the previous i and j values, and may be a single digit. The streamer part is the streamer's username, and it indicates what stream is being requested. The quality value lists what the requested quality for the stream is, i.e., high, medium, low, mobile, or chunked if the default ('source') option is being used. The l and m values are numbers that do not change for the streamer's current broadcast; they do change if the streamer stops broadcasting and then restarts at a later date. The n value is a sequential number that specifies the latest part of the requested stream, and the h value seems to be a hash value for the file. The Bro HTTP logs capture all of these requests, and lists the referrer as the URL for the streamer's page.

Table 6.1: Twitch Live-stream Content Volumes

	Total	`twitch.tv`	Percent	`ttvnw.net`	Percent
December	2.82 TB	2.81 TB	99%	2.44 GB	1%
January	3.14 TB	3.13 TB	99%	3.96 GB	1%
February	3.74 TB	3.74 TB	99%	1.71 GB	1%
March	4.79 TB	2.67 TB	56%	2.13 TB	44%
April	3.74 TB	0.00 MB	0.0%	3.74 TB	100%

The total live-streamed volume from Twitch[3] is 18.23 TB, much lower than the volumes observed from services such as YouTube or NetFlix. There are two explanations for this. First, Twitch is not as popular as the other services. Second, viewers can only view live-streamed content when the streamer is streaming, thus the catalogue of content is more

[3]Twitch switched to serving video through the `ttvnw.net` domain on March 16th.

limited. A monthly breakdown of Twich live-stream volume (by host) is provided in Table 6.1.

Over the five-month period, we observed 6,677 different streamers broadcasting live on Twitch; another 92 streamers were accessed with a live-stream URI, but did not transmit any bytes. The top 41 streamers are responsible for transmitting over 50% of the bytes, while the top 229 transmitted 80% of the bytes. Figure 6.1 shows the cumulative volume (for the entire observation period) over the number of streams. Once more, we can see a long-tail distribution for streams; a small number of streams provide a majority of the volume.

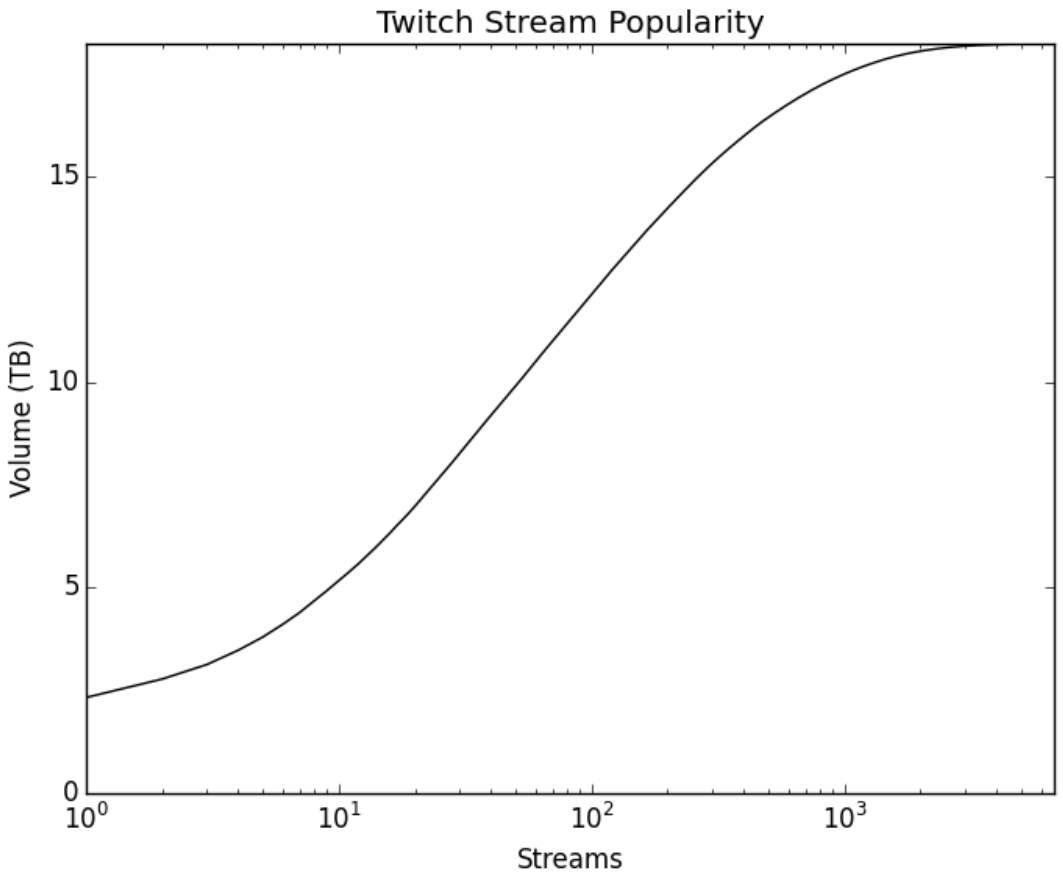


Figure 6.1: Twitch Live-Stream Popularity

Table 6.2 shows the overall top 20 live-streamed channels by volume for the observation period. The total traffic these channels sent was 6.83 TB (37.45% of total live-stream).

Table 6.2: Twitch Top 20 Live-Streamers; rank by month

Stream	Volume	December	January	February	March	April
1. riotgames	1.68 TB	338	1	1	1	1
2. beyondthesummit	649.08 GB	2	2	2	14	5
3. imaqtpie	449.93 GB	13	5	3	4	4
4. lirik	350.81 GB	7	3	13	13	8
5. nl_kripp	349.57 GB	5	8	5	22	2
6. esltv_lol	319.15 GB	1	27	-	-	-
7. trumpsc	311.13 GB	6	7	8	10	9
8. summit1g	286.35 GB	8	44	28	6	3
9. tsm_theoddone	286.00 GB	4	11	12	7	22
10. destiny	254.55 GB	3	9	21	20	17
11. esl_lol	234.22 GB	-	-	-	2	1618
12. faceittv	215.58 GB	53	6	9	25	19
13. dotastarladder_en	203.83 GB	35	24	-	5	6
14. amazhs	201.68 GB	9	10	17	38	20
15. clgdoublelift	188.13 GB	20	31	18	21	10
16. forsenlol	184.53 GB	17	18	16	16	31
17. mushisgosu	175.95 GB	42	15	15	9	104
18. flosd	175.62 GB	22	12	6	33	65
19. esl_csgo	156.12 GB	-	-	-	3	61
20. riotgames2	154.01 GB	-	37	19	15	16

Not every stream is active (viewed from campus) each month. Furthermore, we can see that esltv_lol changed their name in February 2015 to esl_tv. There are only 4 streams in this table (out of 19) that appeared in the top 20 for all five months. If we look for streams that appear in the top 20 list for 4 months, we get a list of 10 channels. This shows that there is a set of streams on Twitch that have long-term popularity. For example, riotgames, beyondthesummit, and imaqtpie have been popular throughout our observation period. The low rankings for riotgames and imaqtpie in December could be due to fewer students on campus for that month. The lower position for beyondthesummit in March is easily explained: beyondthesummit focuses on a specific game that had a major tournament (on another channel) in March.

We also see that some channels, such as esltv_lol, show short-term popularity surges. Specifically, attention towards channels playing certain games surges when an eSports com-

petition approaches; we investigate eSports in Section 6.6.

The average amount of traffic per stream for the observation period was 2.73 GB. If we wish to use a localized stream, i.e., transport the stream from Twitch onto the campus network and then re-transmit to viewers, we can use this number to estimate the possible traffic savings. Figure 6.2 shows an estimation of the traffic needed for this. The black line shows the actual volume per stream for the observation period, and the blue dashed line shows our estimated WAN bandwidth consumption for retransmitting popular streams.

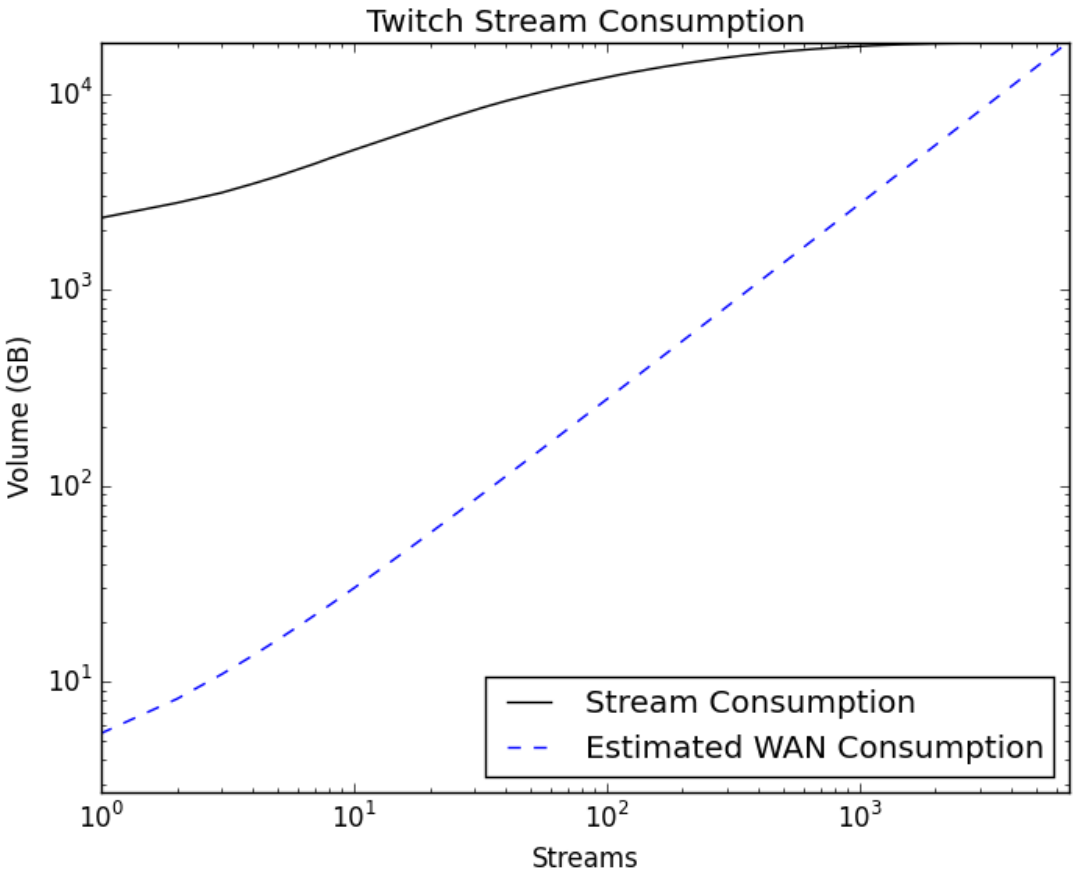


Figure 6.2: Twitch Localized Streaming Traffic Estimation

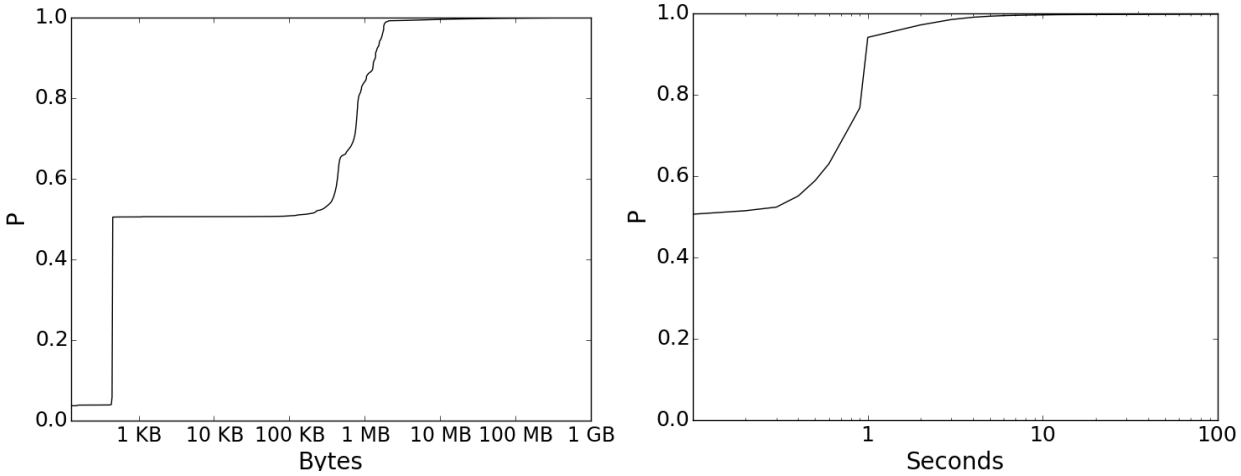
Using Figure 6.2, if we locally retransmitted the top twenty streams (from Table 6.2) our estimate is that they would only have used 54.6 GB of internet traffic for our entire observation period; this would nearly have eliminated this external traffic (reduce by approximately

6 TB). However, these channels transmit significantly more than the average amount, so their impact on bandwidth would be greater than this estimation. It is unlikely that we could implement this form of service easily as it would require multicast functionality in TCP/IP, which is not widely supported in enterprise networks.

Twitch content is served as three-second video clips. The resolution of the clips depends on what is being transmitted. The quality levels range from mobile to 'source'. 'Source' can allow for up to 1920x1080, depending on the resolution of the streamer. High quality is for clips with 1280x720 resolution, medium is 852x480, low is 640x380, and mobile is 400x226.

Over the entire observation period, most requests are made for the 'source' resolution. In fact, 43.0% of requests were made for source, 33.7% were made for high, 19.9% were for medium, 2.63% were for low, 0.57% were for mobile, and 0.18% were audio only. Regardless of quality, response durations last less than one second to keep up with the live-stream.

Detailed analysis of live-streamed traffic is provided in Sections 6.2 through 6.5. The general volumes for this type of traffic are shown in Table 6.1. Twitch also offers VOD content, which we examine in Appendix H since it is much lower in volume than live streamed content.



(a) Size CDF (b) Duration CDF

Figure 6.3: December 2014 - April 2015 Twitch HLS Response Characteristics

Requests for live-stream content from Twitch all have a body length and duration of zero. Responses, on the other hand, are more varied. The size of the response depends on the requested quality; high resolution videos can be very large. Figure 6.3a shows the response size CDF for Twitch. There is a definite step behaviour in this graph. This is due to browsers interacting with Apple HLS making two requests: one returns the video content, and the other does not. The second request results in a much smaller `Application/vnd.apple.mpegurl` response.

Figure 6.3b shows the response duration CDF for HLS content. Most of the responses finish in less than one second. In this case, having very quick responses is important to the quality of the content. If the response takes too long, then the user experience is greatly diminished.

6.1.1 Hosting

A streamer may 'host' another streamer. We refer to the user whose content is being streamed as the streamer, and the user who is hosting the streamer as the host. When this takes place, the host will broadcast the streamer's content. We can detect when a streamer is being hosted in the Bro logs, since the referrer fields of the HTTP request-response pairs indicates the host and not the streamer.

We see some traffic where one streamer is hosting another. The overall volume of this is pretty low. In December 2014, this amounted to 20.84 GB. In January 2015, it was 47.36 GB, February was 61.18 GB, March was 64.33 GB, and finally, in April it was 58.87 GB. The most bytes viewed from a single host-streamer pair in a month was in January when 7.12 GB was transferred.

6.2 Monthly Traffic

Table 6.3 shows a monthly connection summary. Around 300 KB are uploaded in each connection; this is similar to NetFlix's behaviour of sending mostly (HTTP and TCP) headers. Once more, around 20 MB per connection is used to transport content from Twitch. The connection duration averages around two minutes. Like with NetFlix traffic, a viewer will use multiple connections when viewing a stream for an extended duration.

Table 6.3: Twitch Connection Summary

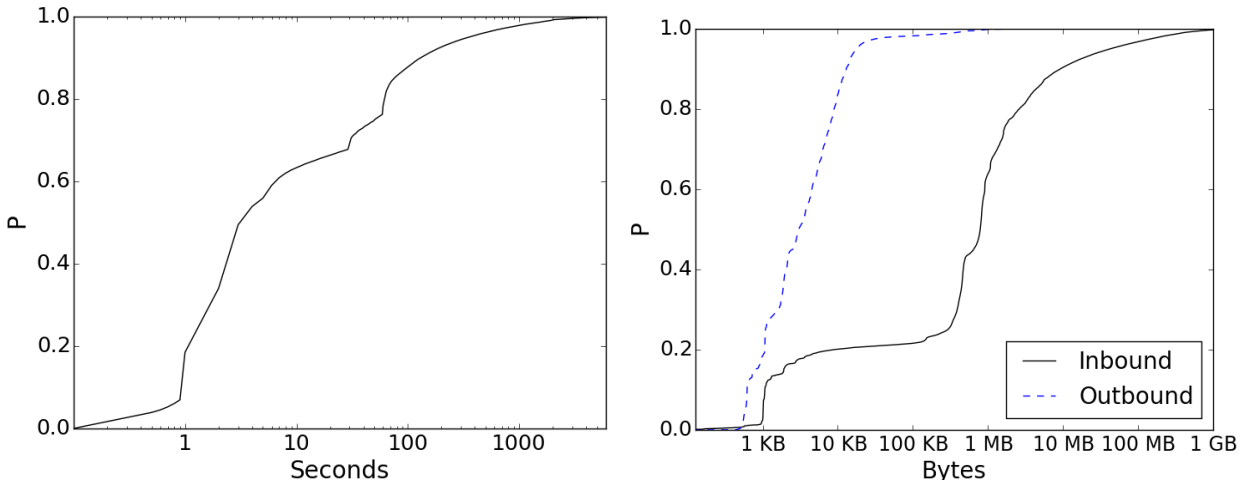
	Connections	Avg. Outbound Vol	Avg. Inbound Vol	Avg. Duration
December	204,499	307.6 KB	22.67 MB	118 s.
January	288,198	312.8 KB	22.22 MB	114 s.
February	321,664	275.7 KB	20.46 MB	100 s.
March	429,370	284.2 KB	21.63 MB	116 s.
April	308,894	277.2 KB	23.38 MB	132 s.

Figure 6.4a shows the connection duration CDF for the complete observation period. All connections to Twitch are included in this diagram; live-streams, VOD content, as well as requests for static elements (the only thing not included is Chat). Compared to the average connection duration for video content (in Chapter 4), we can see that Twitch connections have a slightly shorter duration. When compared to NetFlix connections, the effect is more visible; this may be due to Twitch using a connection to load a small image, i.e., an emoticon used in the chat panel.

Figure 6.4b shows the CDF for connection size. Here, we can see that the inbound traffic from Twitch exhibits a behaviour that is much more step-like. This may be due to users checking a specific stream that is offline – thus not a lot of data is transferred.

Over the entire observation period, we have observed 25 different content type headers used by Twitch domains. The five most popular by bytes transferred are shown in Table 6.4.

There is a large difference between the volumes used to transport content from the Apple HLS servers, and the other content types. There is also a large difference between



(a) Duration CDF

(b) Size CDF

Figure 6.4: Twitch Connection Characteristics December 2014 - April 2015

Table 6.4: Twitch Content Types by Volume

	Type	Percent	Volume
1	`Video/mp2t`	39.1%	18.68 TB
2	`Video/x-flv`	0.02%	719.00 GB
3	`Application/javascript`	0.05%	35.80 GB
4	`Text/html`	1.09%	27.74 GB
5	`Application/json`	9.20%	12.66 GB

Percent is of Twitch Requests

Flash content (old VOD type or used for ads) and the other types. Content from Apple HLS servers dominate the responses, both in number and volume. In fact, the sixth ranked response by volume is also associated with the HLS servers. The content type `Application/vnd.apple.mpegurl` was present in 37.8% of the responses, and accounted for 8.95 GB of volume.

6.3 Twitch Usage Patterns

Unlike other video traffic, the nightly drop-off in Twitch traffic occurs earlier. In fact, by 23:00 there is a sharp decrease. This is due to the live-streamed nature of the content. The fact that there is an earlier drop-off and very little traffic in the idle period, from 23:00-10:00,

suggests that the most viewed streamers are somewhere in North America. We can see that the peak traffic period for Twitch occurs from 12:00-18:00. We also can see that virtually no traffic is sent to the common Twitch domains from the University of Calgary's network.

Figure 6.5 shows the Twitch traffic levels for December 2014. The bytes being counted in these graphs are all HTTP connections to Twitch domains (excluding chat). The last two weeks of December are the holiday break, so traffic levels are very low.

In December, we observed 191,348 connections for Twitch live-stream content and 9,277 for VOD. We did not see a lot of bytes going to Twitch HTTP servers. This may indicate that no one on campus is streaming content, or that uploading a stream uses another server (or does not use HTTP).

Table 6.5: Twitch Top Streamers - December 2014

Stream	Req. Count	Percent of requests	Volume
esltv_lol	607,903	9.00%	295.8 GB
beyondthesummit	422,771	6.26%	200.2 GB
destiny	124,263	1.84%	84.1 GB
tsm_theoddone	148,538	2.20%	67.2 GB
nl_kripp	171,706	2.54%	61.9 GB
trumpsc	174,365	2.58%	58.3 GB
lirik	94,590	1.40%	50.0 GB
summit1g	67,333	1.00%	48.6 GB
amazhs	137,388	2.01%	45.4 GB
twitchplayspokemon	172916	2.56%	38.7 GB

Table 6.5 shows the top ten streamers (by volume) for December. esltv_lol is the stream for an eSports league for *League of Legends*. The esltv_lol is the first example of an eSports event stream on Twitch (since it broadcasted a tournament). eSports games are discussed in Section 6.6. The beyondthesummit stream focuses on a game called *Dota 2*. The streams destiny, tsm_theoddone, nl_kripp, trumpsc, lirik, summit1g, and amazhs are streams for players. The twitchplayspokemon channel was a channel Twitch set up where viewers could play Pokemon by providing input through chat.

Figure 6.6 shows Twitch traffic in January 2015. The first week of January is "block

week" for the university, so traffic is lower. On January 30th, there was an interruption on the Campus network.

In January, there were 268,748 connections for Twitch live-stream content and 16,574 for VOD content.

Table 6.6: Twitch Top Streamers - January 2015

Stream	Req. Count	Percent of requests	Volume
riotgames	807,969	10.84%	301.4 GB
beyondthesummit	324,023	4.35%	181.7 GB
lirik	232,547	3.12%	134.2 GB
gamesdonequick	188,816	2.53%	122.0 GB
imaqtpie	229,622	3.08%	102.3 GB
faceittv	181,526	2.44%	71.6 GB
trumpsc	181,788	2.44%	71.4 GB
nl_kripp	186,513	2.50%	70.1 GB
destiny	72,051	0.97%	50.7 GB
amazhs	139,443	1.87%	45.7 GB

Table 6.6 has the top streams for January. The bold entries correspond to streams that have not been seen in previous months. The riotgames stream, owned by Riot (the developers for *League of Legends*), focuses on covering eSports events for their game. The gamesdonequick stream is a stream to raise money for charity, representing another event stream. This stream focuses on speed-running games (beating a game quickly) for charity; they held a marathon drive in January. imaqtpie is another stream for a single player and faceittv has competitions for many games.

Figure 6.7 shows Twitch traffic for February 2015. There was a failure with Bro on the 2nd. High activity levels, such as the 21st, are normally due to eSports events. In this case, *League of Legends* was having a tournament.

In February, we saw 287,746 connections for Twitch live-stream content, and 17,912 for VOD content.

Table 6.7 shows the top streams for February. Most of the streams have been seen in previous months. This streamhouse channel is operated by a group of people who have

Table 6.7: Twitch Top Streamers - February 2015

Stream	Req. Count	Percent of requests	Volume
riotgames	1,329,438	14.99%	572.0 GB
beyondthesummit	272,965	3.08%	151.2 GB
imaqtpie	251,305	2.83%	119.2 GB
streamerhouse	236,292	2.66%	89.0 GB
nl_kripp	222,546	2.51%	75.3 GB
flosd	91,960	1.04%	65.6 GB
nightblue3	221,058	2.49%	59.9 GB
trumpsc	144,338	1.63%	59.8 GB
faceittv	140,096	1.58%	59.0 GB
filtersc	79,350	0.89%	56.8 GB

installed IP-webcams in their house. Viewers can watch them play games and watch them go about their daily activities. The other new streams, flosd, nightblue2, and filtersc, are player channels.

Figure 6.8 shows Twitch traffic for March 2015. From March 12-14, a major eSports tournament was held; we investigate this in depth in Section 6.6.

In March, we observed 400,825 connections for Twitch live-stream content, and 26,935 for VOD content.

Table 6.8: Twitch Top Streamers - March 2015

Stream	Req. Count	Percent of requests	Volume
riotgames	1,115,189	9.62%	438.5 GB
esl_lol	475,003	4.10%	234.2 GB
esl_csgo	308,322	2.66%	144.1 GB
imaqtpie	277,808	2.40%	127.4 GB
dotastarladder_en	192,266	1.66%	98.6 GB
summit1g	193,088	1.66%	96.5 GB
tsm_theoddone	181,026	1.56%	80.9 GB
ultra	168,499	1.45%	76.4 GB
mushisgoru	123,259	1.06%	69.9 GB
trumpsc	170,077	1.47%	63.8 GB

The top streams for March are listed in Table 6.8. March is interesting since it includes many new channels focused on eSports. The channels esl_lol and esl_csgo are provided by the eSports league to cover *League of Legends* and *Counter Strike: Global Offensive*, respectively.

The viewing of esl_csgo is covered in depth in Section 6.6. Note that we are not counting else_lol as a new channel since it was renamed from esltv_lol. The dotastarladder_en channel focuses on covering their own *Dota 2* competitive league. The other two new channels are ultra and mushisgoru, a stream for a music festival and a player's stream, respectively.

Figure 6.9 shows Twitch traffic for April 2015. On the 10th-11th, there was a failure with Bro. On the 29th, our observation period ended. In April, there were 263,045 connections to Twitch for live-stream content and 27,112 for VOD content.

Table 6.9: Twitch Top Streamers - April 2015

Stream	Req. Count	Percent of requests	Volume
riotgames	846,519	8.90%	366.6 GB
nl_kripp	304,308	3.20%	105.0 GB
summit1g	184,793	1.94%	100.7 GB
imaqtpie	167,242	1.76%	66.3 GB
beyondthesummit	127,427	1.34%	63.4 GB
dotastarladder_en	120,950	1.27%	62.4 GB
hegemonytv	92,014	0.97%	60.1 GB
lirik	176,677	1.86%	59.9 GB
trumpsc	161,990	1.70%	57.8 GB
clgdoublelift	198.048	2.08%	57.2 GB

The top streams for April are in Table 6.9. Here, we can see that most coverage of eSports from March has decreased. The new streams for the month, hegemonytv and clgdoublelift, are both player streams.

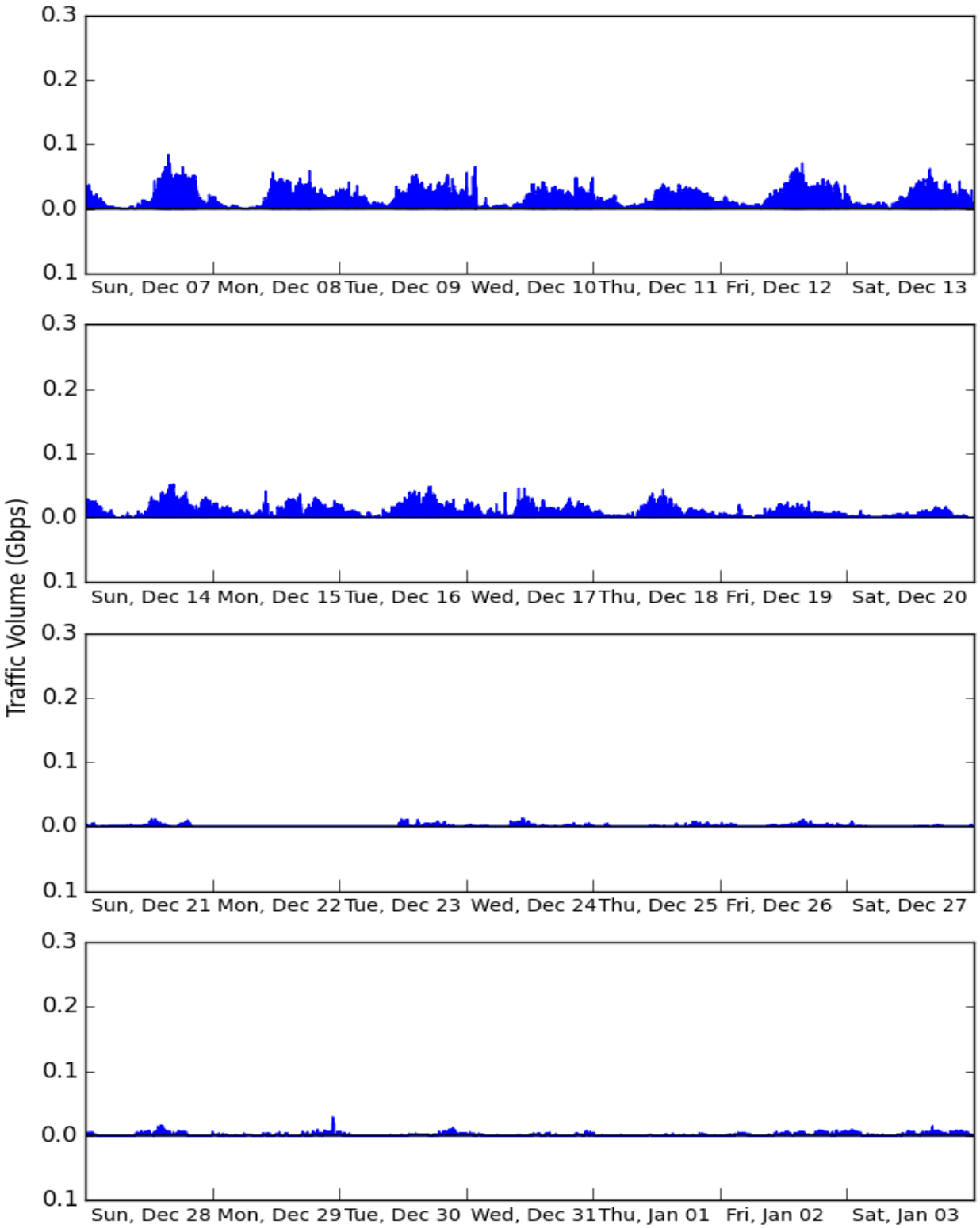


Figure 6.5: Twitch Traffic for December 2014

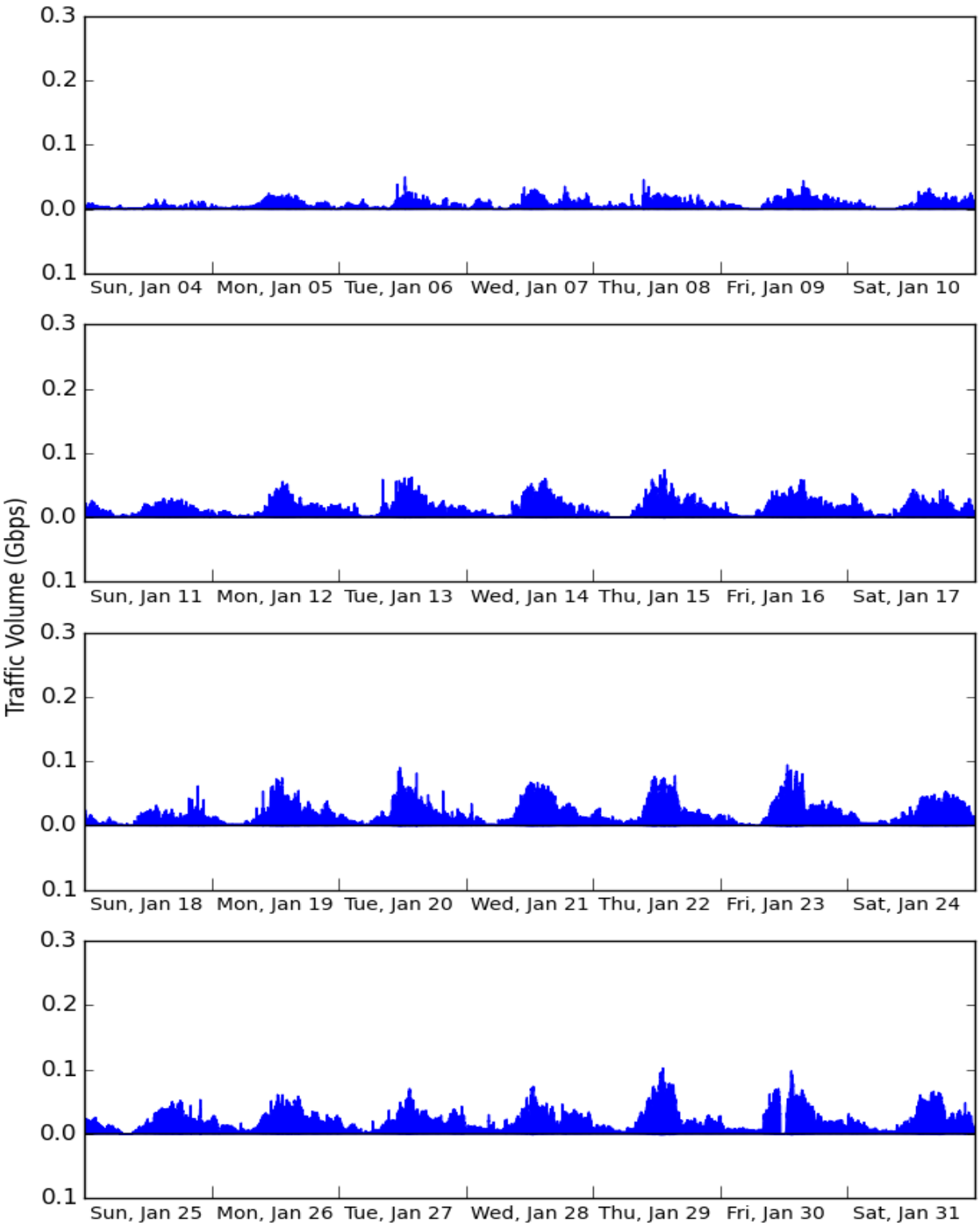


Figure 6.6: Twitch Traffic for January 2015

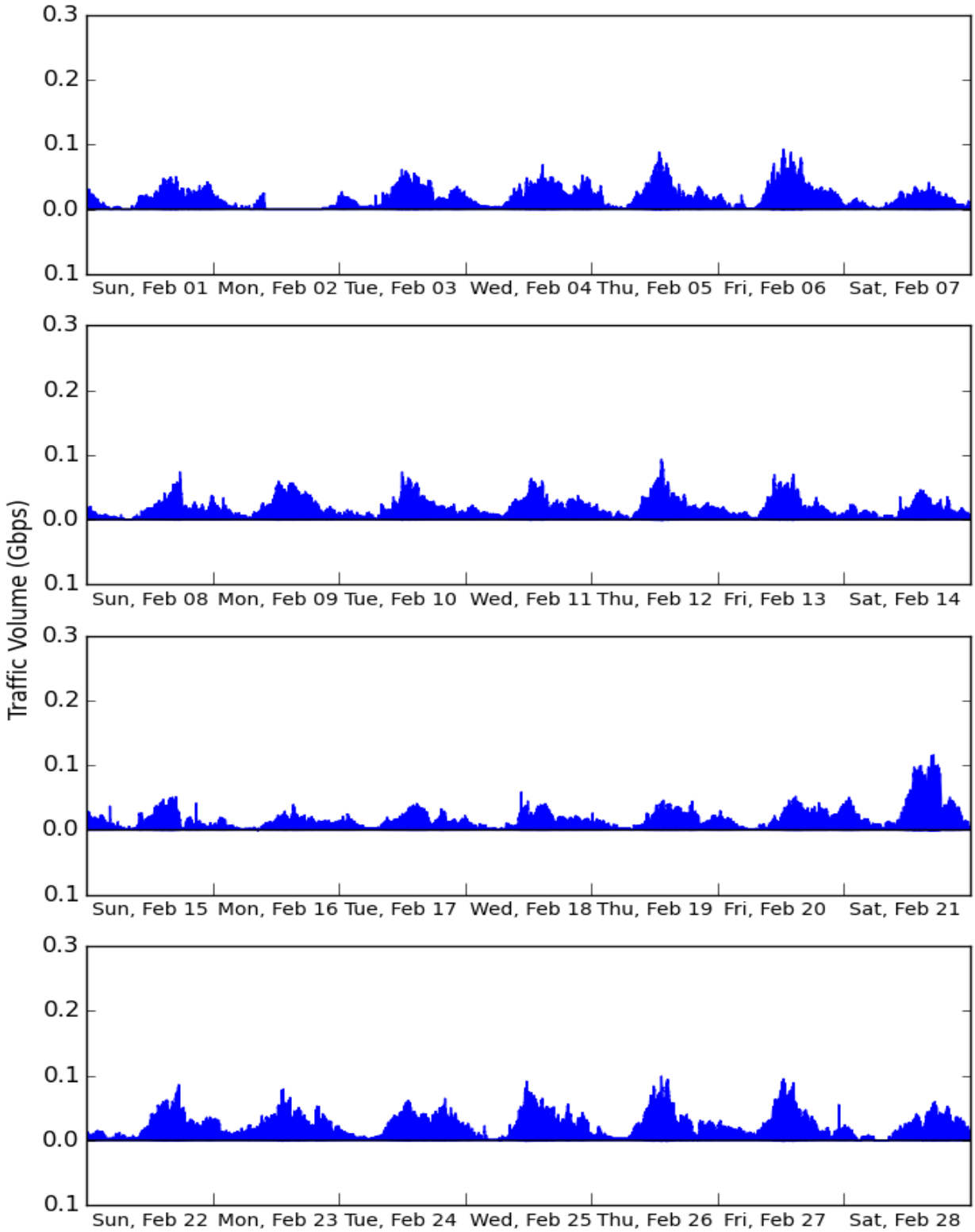


Figure 6.7: Twitch Traffic for February 2015

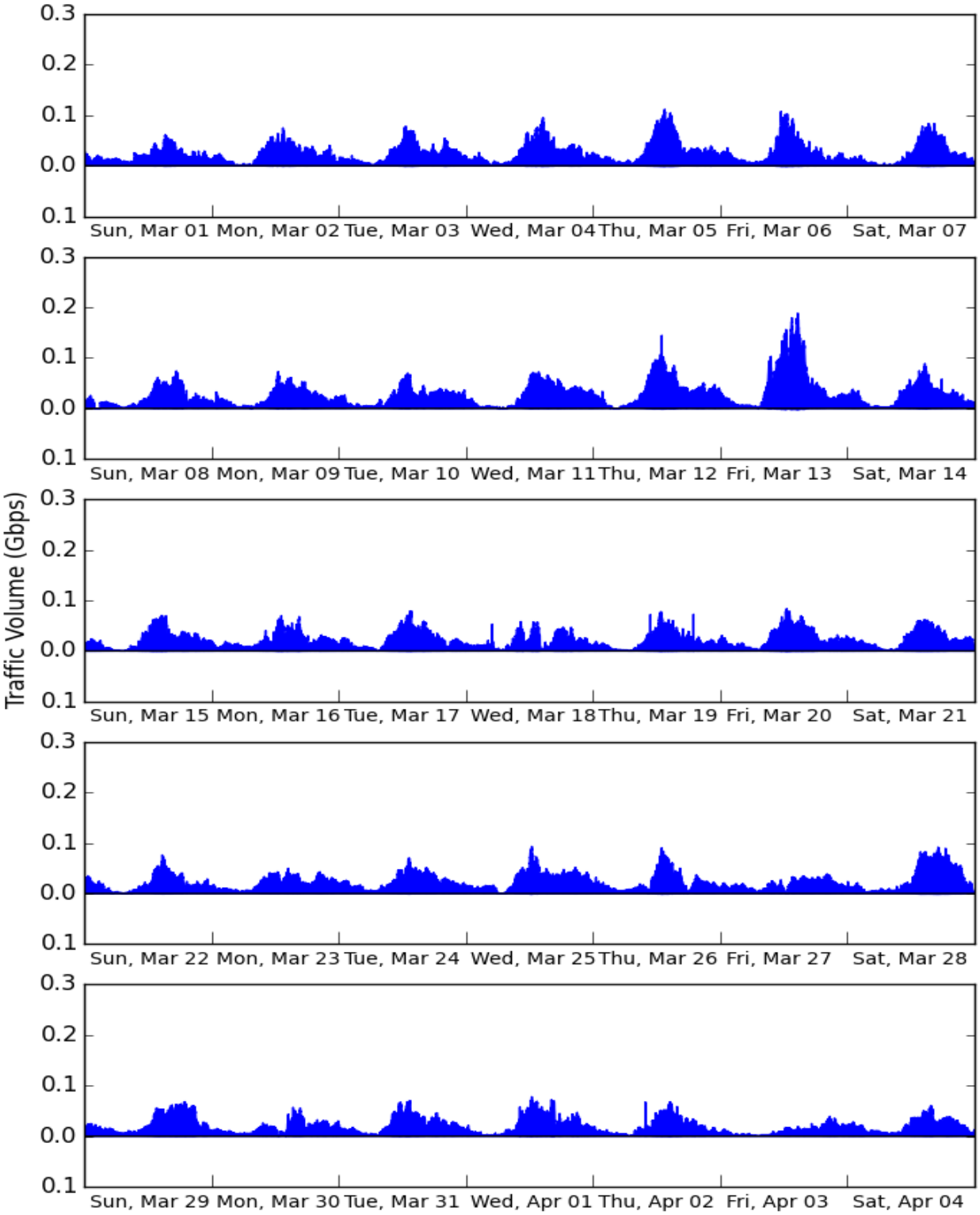


Figure 6.8: Twitch Traffic for March 2015

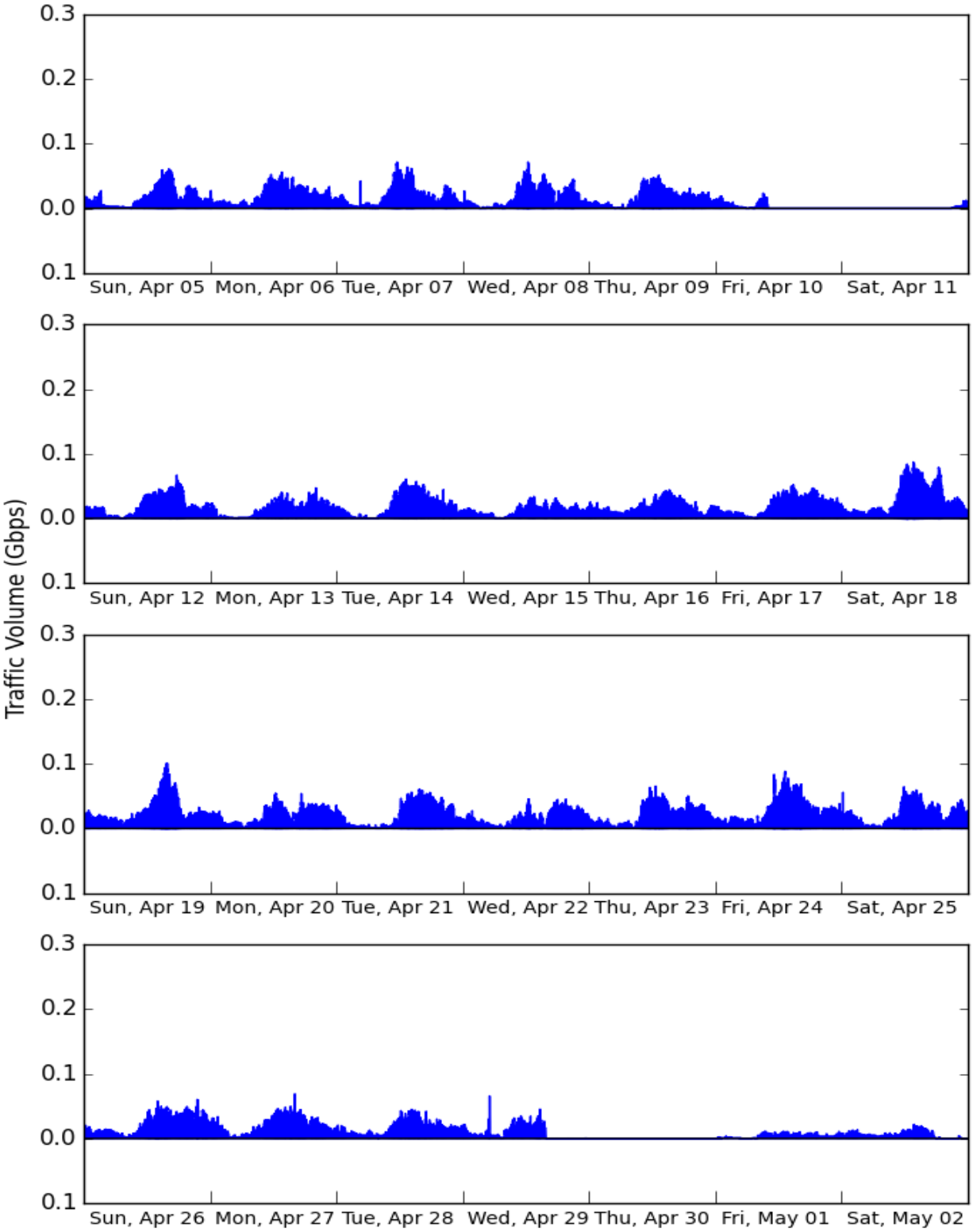


Figure 6.9: Twitch Traffic for April 2015

6.4 Weekly Traffic

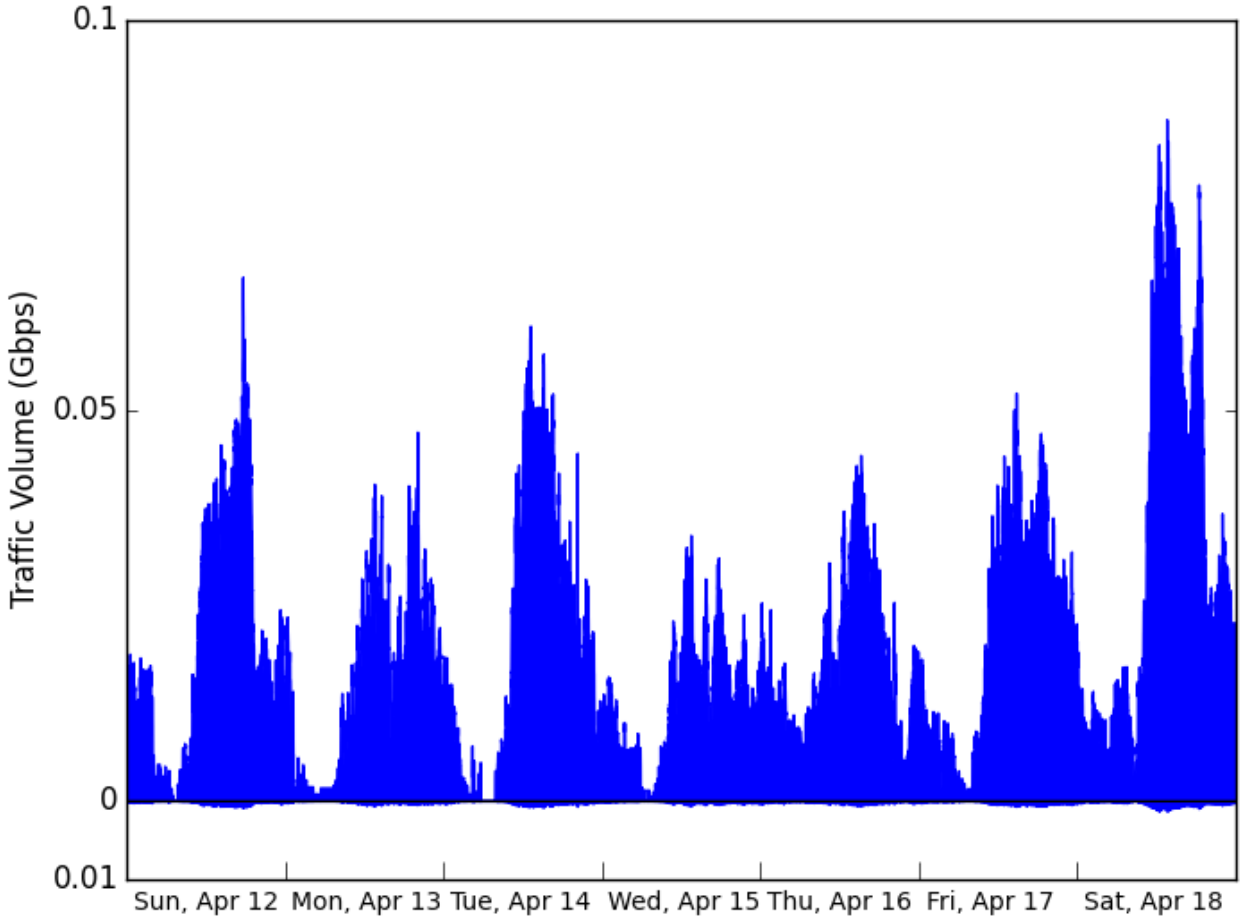


Figure 6.10: Twitch Weekly Traffic April 12-18, 2015

Figure 6.10 shows the weekly traffic for Twitch from April 12 to April 18. This week was chosen since it represents a normal week for traffic, and for consistency - we used the same week for studying NetFlix traffic in Chapter 5. Once again, we find that traffic exhibits a diurnal pattern.

Table 6.10 shows the weekly stats for live-stream and VOD content. April 18th had a spike of traffic. This was mostly driven by increased traffic to the riotgames stream, and the esea stream that covers *Counter Strike: Global Offensive*. Unlike other traffic, there does not seem to be a difference between weekday and weekend traffic for Twitch.

The top five channels for the week are outlined in Table 6.11. When looking at individual

Table 6.10: Twitch Weekly Traffic Summary April 12-18, 2015

	Live-stream Connections	Live-stream Volume	VOD Connections	VOD Volume
April 12	8,602	149.6 GB	0	0
April 13	6,529	104.7 GB	690	3.284 GB
April 14	12,093	127.8 GB	433	2.176 GB
April 15	13,664	97.54 GB	301	982.3 MB
April 16	5,257	109.9 GB	698	3.693 GB
April 17	9,072	130.7 GB	1,764	8.406 GB
April 18	8,957	252.0 GB	196	1.225 GB

Table 6.11: Twitch Top Streams April 12-18, 2015

	1	2	3
April 12	riotgames 46.59 GB	showdownsmash 17.13 GB	hegemonytv 7.257 GB
April 13	qwertycopter 6.722 GB	lirik 6.177 GB	aftonbladetesport 5.233 GB
April 14	faceittv 10.03 GB	hegemonytv 7.224 GB	admiralbulldog 5.331 GB
April 15	nl_kripp 7.286 GB	faceittv 6.885 GB	beyondthesummit 4.758 GB
April 16	darklordsen 11.62 GB	trumpsc 6.829 GB	riotgames2 6.386
April 17	esea 18.37 GB	redbullesports 17.41 GB	summit1g 6.671 GB
April 18	riotgames 72.46 GB	esea 22.68 GB	hegemonytv 14.17 GB
	4	5	
April 12	esl_hearthstone 6.857 GB	esl_csgo 4.946 GB	
April 13	imaqtpie 3.114 GB	trick2g 2.981 GB	
April 14	trick2g 4.509 GB	clgdoublelift 4.014 GB	
April 15	eg_jwong 3.945 GB	blizzheroes 3.635 GB	
April 16	redbullesports 3.807 GB	poiisondn 3.659 GB	
April 17	saintvicious 4.080 GB	sjow 4.024 GB	
April 18	gfinitytv 11.45 GB	poiisondn 6.956 GB	

streams, there is an increase in traffic levels on the weekend. That is, top streams transmit more on weekends than weekdays. We can also see that there are 28 channels that reach the top five in a week. This high flux for popular channels in a given day makes it difficult to predict what streams will be popular, since only 13 of these channels appear in Table 6.2.

6.5 Daily Traffic

Once again, we investigate the traffic on April 14th. On the 14th, the total number of connections to Twitch was 21,471. The average inbound bytes per connection was 9.999 MB, outbound was 118.6 KB, with an average duration of 75.2 seconds. Out of these connections,

12,093 were used to transport live-stream content, 433 transported VOD content, and 36 transported Flash (VOD) content. 127.8 GB of live-stream content was transported in 374,572 responses, 2.176 GB of VOD content took 2,106 responses, and the Flash (VOD) content used 39 responses to transport 1.019 GB.

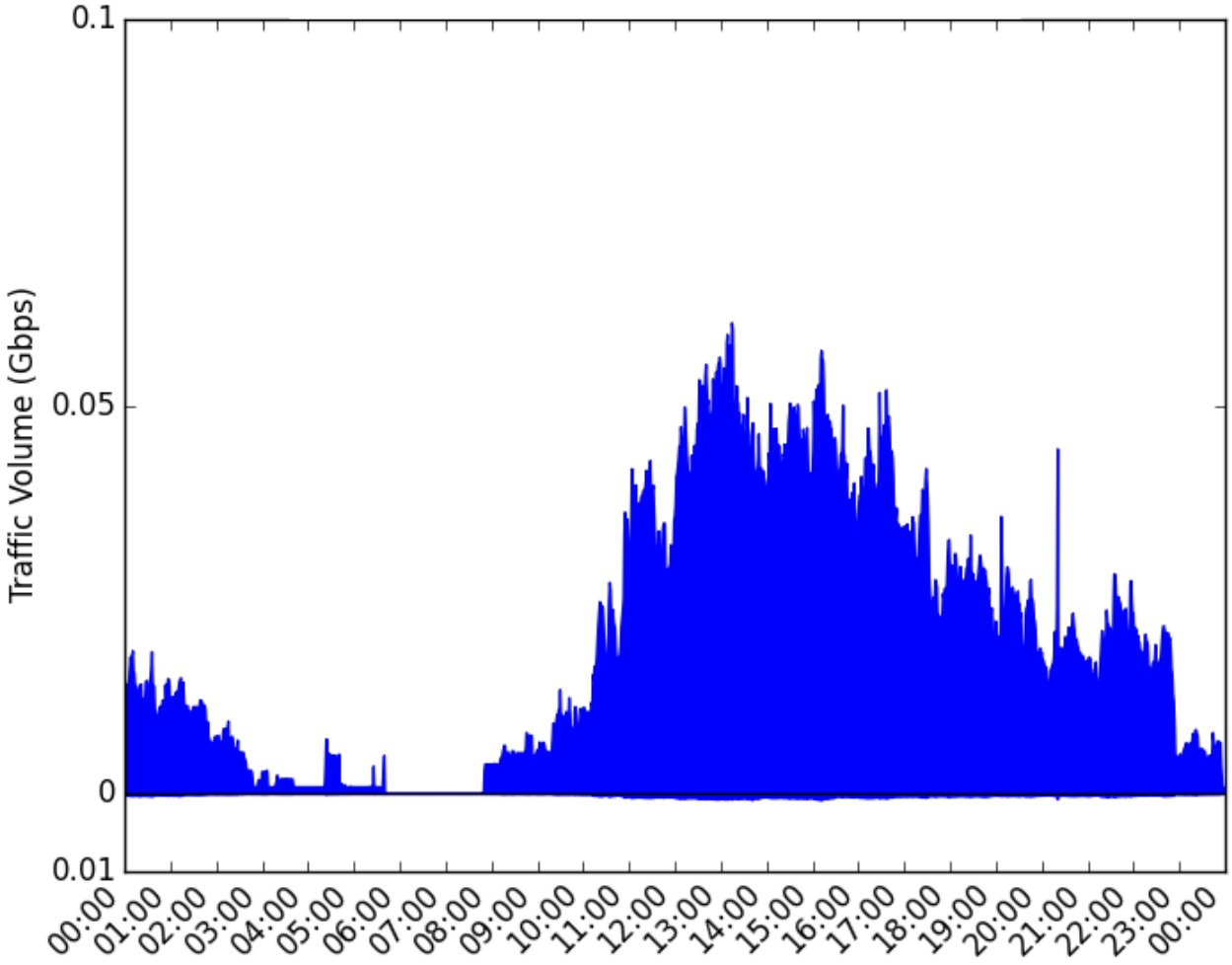


Figure 6.11: Twitch Daily Traffic Tuesday, April 14, 2015

The daily traffic is illustrated in Figure 6.11.

6.6 eSports

Twitch often hosts streams from eSports tournaments. The most popular games for eSports are the following: *League of Legends* (LoL)[4], *Dota 2*, *Starcraft 2* (SC2), *Hearthstone*, and *Counter Strike: Global Offensive* (CS:GO). *Dota 2* and LoL are team-based multi-player online battle arena (MOBA) games. *Hearthstone* is an online card game. CS:GO is a team-based first person shooter (FPS) and SC2 is a real-time strategy (RTS) game.

Dota 2 was released to the public on July 9, 2013, following an ongoing beta period that started in 2011. *League of Legends* was released on October 27, 2009; its beta stage started on April 10 of the same year. *Counter Strike: Global Offensive* was released on August 21, 2012. *Starcraft 2* was released on July 27, 2010, and the first expansion to the game titled *Heart of the Swarm*, was released on March 12, 2013. A second expansion titled *Legacy of the Void* is currently being developed. When eSports matches for SC2 are played, they are played with the latest expansions and updates to the game.

MOBA games started as custom maps for RTS games, the most famous being the *Defense Of The Ancients* (DOTA) map for *WarCraft 3*. Unlike a typical RTS game, in a MOBA game a player controls a single character. In a MOBA game, two teams of five players each compete against each other. A team wins by destroying the other team's base. *Dota 2* is regarded as having a higher skill ceiling than LoL.

A majority of eSports events are based on PC games. LoL, *Dota 2*, and CS:GO are all team-based games where two teams of 5 players each compete against each other. SC2 has support for team-based games, but is played 1 on 1 at eSports events. In eSports events, it is common for each round to be played as a series (i.e., best of 7).

[4]These terms are listed in the List of Symbols.

6.6.1 Case Study: ESL-One Katowice

In this subsection, we present a case study for a major eSports tournament. We investigate the eSports league (ESL) CS:GO tournament that was held in Katowice, Poland on March 12-15, 2015. This tournament had 16 teams that competed in a group stage, then a playoff series. This specific tournament was part of the greater Intel Extreme Masters (IEM) Tournament held in Katowice [32]. The group stage was a double-elimination, best of one format, i.e., two out of four teams from each group advance; to advance they must win two matches. Each round of the playoffs was a single-elimination best-of-three series. The first place prize pool for the winning team in this tournament was $100,000 (USD).

When studying this event, we use network-level measurements from our monitor, as well as statistics provided by third-party sources.

Third-Party Measurements

Using measurements obtained by third-party sources, we may construct a view of global traffic on Twitch. ESL provided a basic info-graphic [53] with information about viewers to the event. The information from this info-graphic that we are interested in is as follows: 36.95 million total Twitch sessions, 8.79 million unique Twitch viewers, 16 million hours of content broadcast via Twitch, and a peak of 1.012 million concurrent viewers (in Twitch and in game).

Using data from another third-party site[5], we can determine how popular this event was on Twitch. This second dataset uses data taken from Twitch's public API at ten-minute intervals. Figures 6.12 through 6.14 are provided by this dataset.

Figures 6.12 and 6.13 show the number of viewers on Twitch over time in blue. Figure 6.12a shows that the most concurrent viewers on Twitch occurred on March 13, 2015 with just over 1.5 million viewers. Figures 6.12b and 6.12c show concurrent viewers for Twitch and CS:GO, respectively, for our observation period. They clearly show a spike in

[5] `stats.twitchapps.com`

CS:GO activity for the ESL-One tournament. Figure 6.14 shows activity for the week of March 10-17, 2015; at this scale one can easily see the diurnal patterns of Twitch. The activity of the tournament is clearly visible as well. There is a spike (of multiple orders of magnitude) in viewership for CS:GO when the tournament takes place. During the tournament, Twitch has more concurrent viewers than during the preceding days, and the days following it. We can safely assume that the new viewers visited Twitch to view the event.

Finally, Figure 6.13 shows Twitch viewership for the event duration. While looking at the days for the event, we can easily see diurnal activity for Twitch as a whole. When looking at CS:GO viewers and the official ESL channel viewers, we also see multiple local peaks per day. This corresponds to matches in the tournament, not network or service failures.

Using the information from Figure 6.13, we find that CS:GO had over 840,000 concurrent viewers, and the esl_csgo channel had nearly 600,000 viewers on March 15, 2015. The fact that the concurrent number of CS:GO viewers is less than what ESL reported could be attributed to a few causes. First, there may have been some channels showing the event that were not labelled as CS:GO. Second, the info-graph also counts in-game (and at-event) spectators. Finally, the peak number may be missed due to the ten-minute granularity of the second dataset. The difference in viewers between the official channel and the overall CS:GO viewers is easily explained, since multiple channels showed CS:GO being played. These channels may be broadcasting localized streams of the matches, other casters providing commentary, or unrelated matches.

Network-Level Measurements

Figure 6.15 shows the University of Calgary's Twitch traffic for the week of the event. It clearly shows a sharp increase in volume for March 12th and 13th.

March 12th had the group elimination phase of the tournament. The first round was on the 13th, and the second round (semi-final) was on the 14th. The finals for the tournament were held on the 15th.

Traffic levels for Twitch and the official eSports League channel are shown in Table 6.12. On March 12th, esl_csgo was the most-viewed channel. The second most-viewed channel was tsm_theoddone, who was a coach for a *League of Legends* tournament occurring at the same time. The third most-viewed channel on the 12th was esl_csgob. Since they were playing concurrent matches in the early phase of the tournament, 12.70 GB of traffic came from that channel. On the 13th, the most viewed channel was esl_lol with 129.9 GB, and esl_csgo was the second-most viewed. The 14th once again had esl_lol as the most-viewed channel with 57.14 GB transferred, and esl_csgo as the second. Finally, on March 15th, esl_csgo was the 15th most-viewed channel, being beaten by the other games of the tournament. *League of Legends* (esl_lol - 47.12 GB), *Hearthstone* (esl_hearthstone - 17.02 GB), and *StarCraft 2* (esl_sc2 - 7.771 GB), were the top three most viewed streams.

Table 6.12: Twitch Live-stream Traffic Summary March 12-15

	Connections	Volume	esl_csgo Volume
March 12	18,435	225.8 GB	53.81 GB
March 13	40,774	322.2 GB	62.32 GB
March 14	6,370	227.5 GB	25.43 GB
March 15	6,120	167.6 GB	2.536 GB

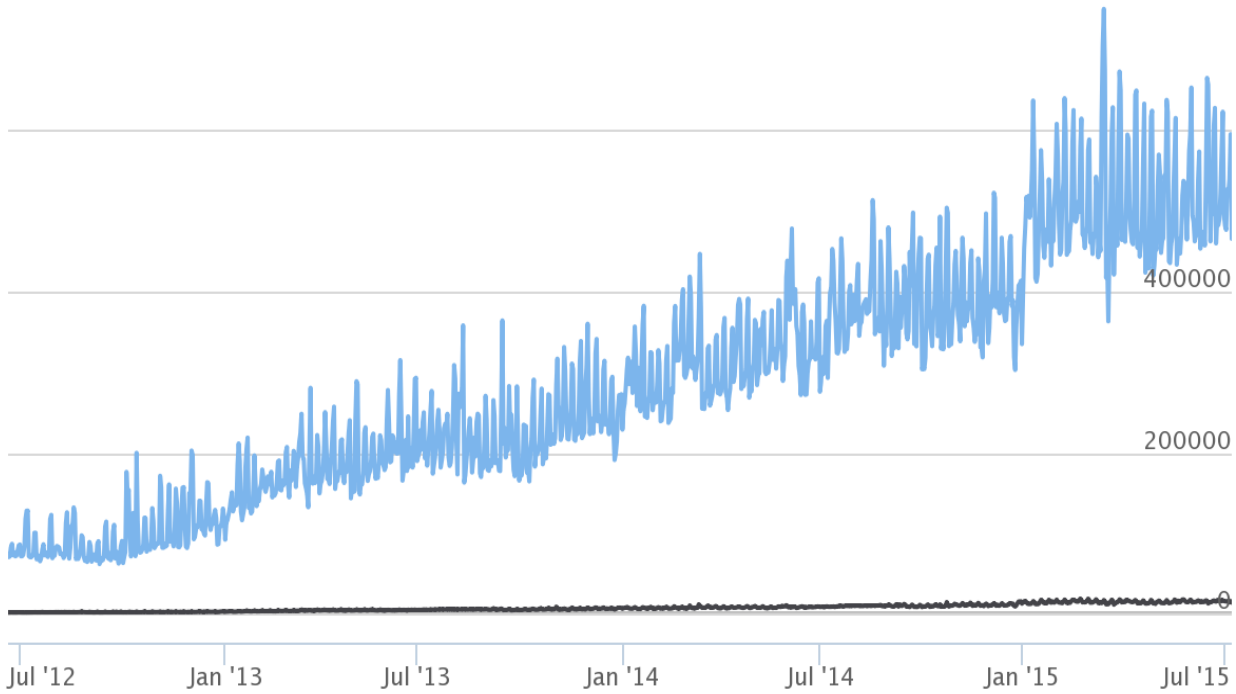
Unlike global Twitch activity, the campus network showed less interest in the *Counter Strike: Global Offensive* tournament. While viewers on campus watched much of the group stage of the tournament, interest lowered as the tournament progressed. Instead, viewers preferred to watch the IEM *League of Legends* matches. This behaviour does not mirror the viewing patterns for popular sports events.

The lowered interest in CS:GO matches over the tournament is easily explained. The important matches, like the finals, for CS:GO were held at 13:00 CEST, which is 05:00 local time. The matches for the other games at IEM were held later, at times more convenient for campus viewers. Another minor contributor to the lower amount of traffic (as a whole on Twitch), is that as the tournaments progressed, fewer matches were played per day.

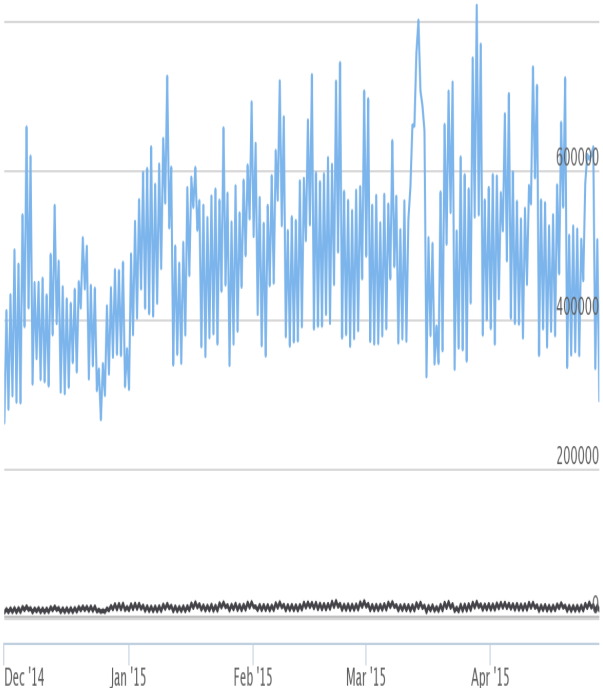
6.7 Summary

In this chapter, we studied Twitch traffic on campus. We explained the volume and characteristics of live-streamed videos. Popular streams on Twitch were characterized and we found that they fell into the same two behaviours that content on NetFlix follows. We estimated the effects of local stream replication on WAN bandwidth. We presented a monthly breakdown of traffic from Twitch, and described weekly and daily traffic specifically. Finally, we investigated viewership of Twitch during one of the largest eSports events Twitch has held to date, and compared our observations to Twitch's global information.

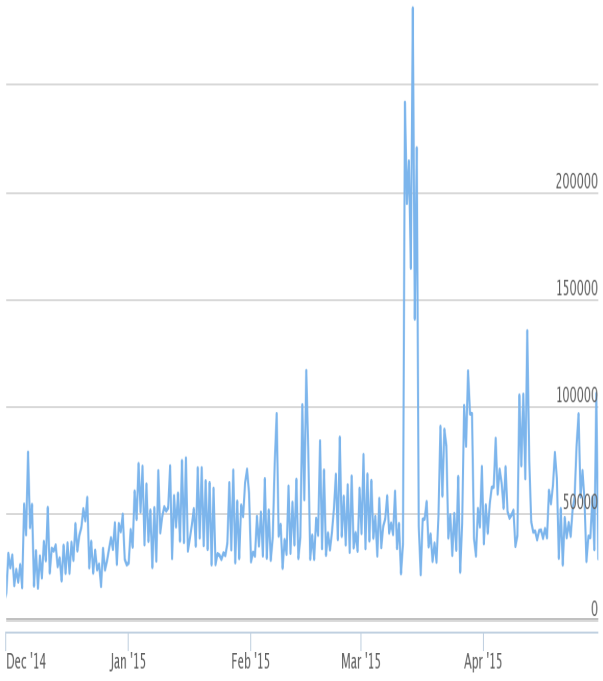
In the next chapter, we present conclusions from our measurement study.



(a) Twitch Viewers by Lifetime (July 2013 – July 2015)

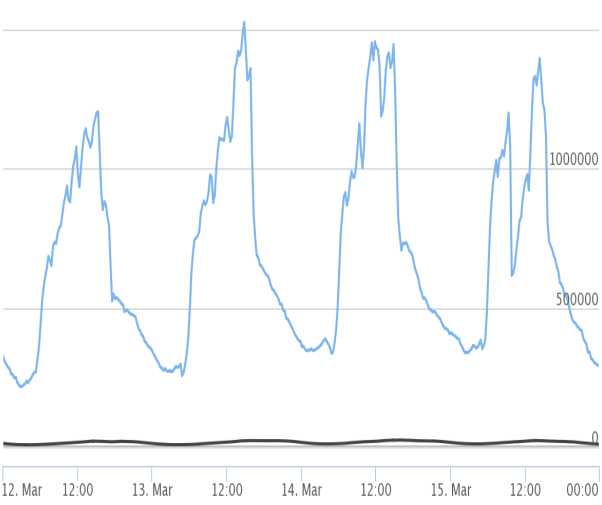


(b) Twitch Viewers Dec 2014 – Apr 2015



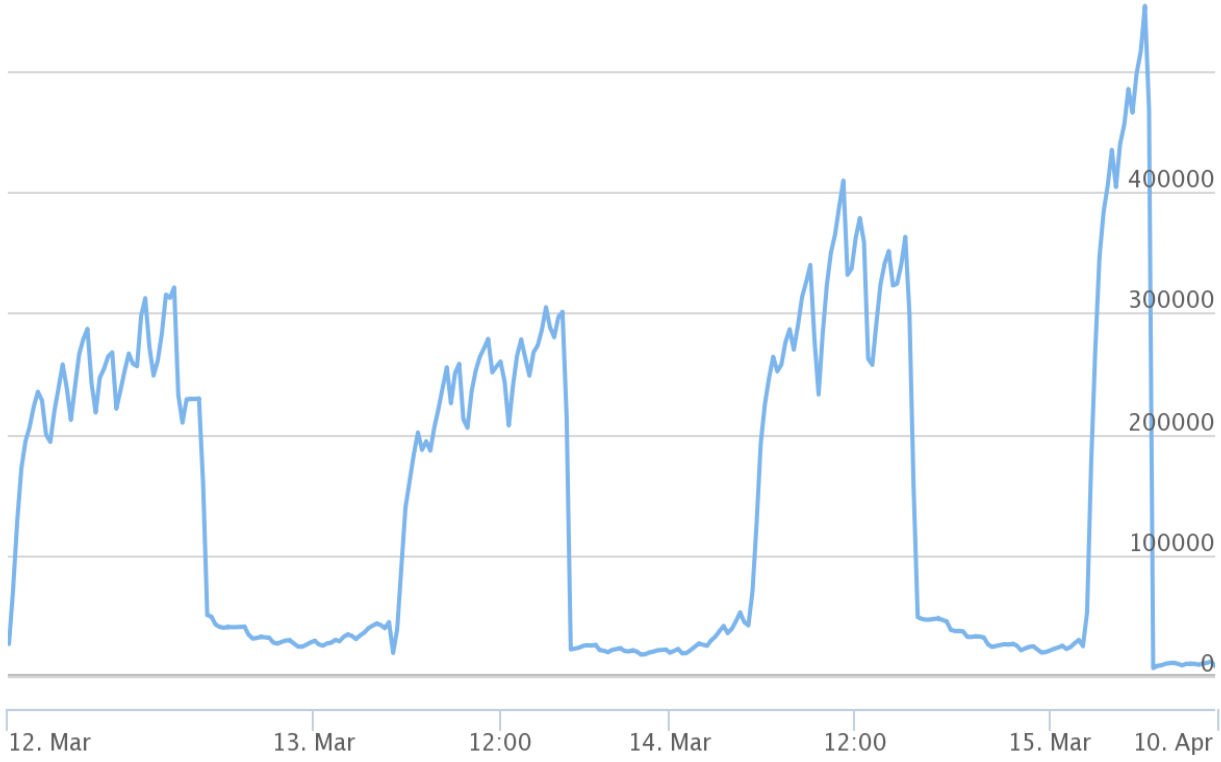
(c) CS:GO Viewers Dec 2014 – Apr 2015

Figure 6.12: Twitch Viewers



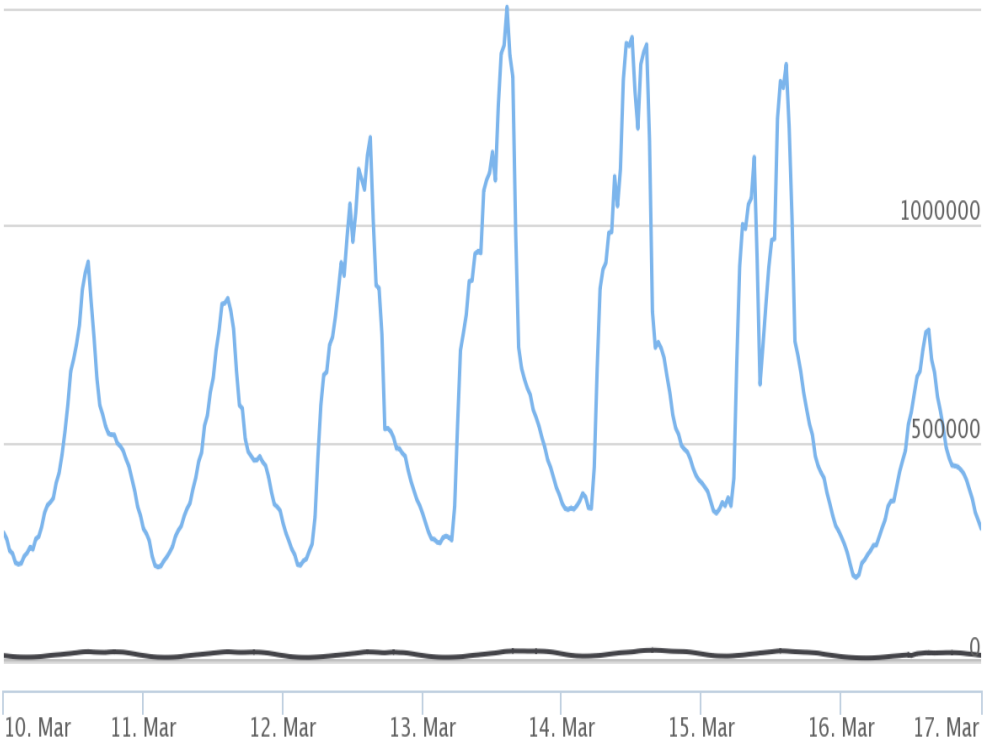
(a) Twitch Viewers March 12-15, 2015

(b) CS:GO Viewers March 12-15, 2015

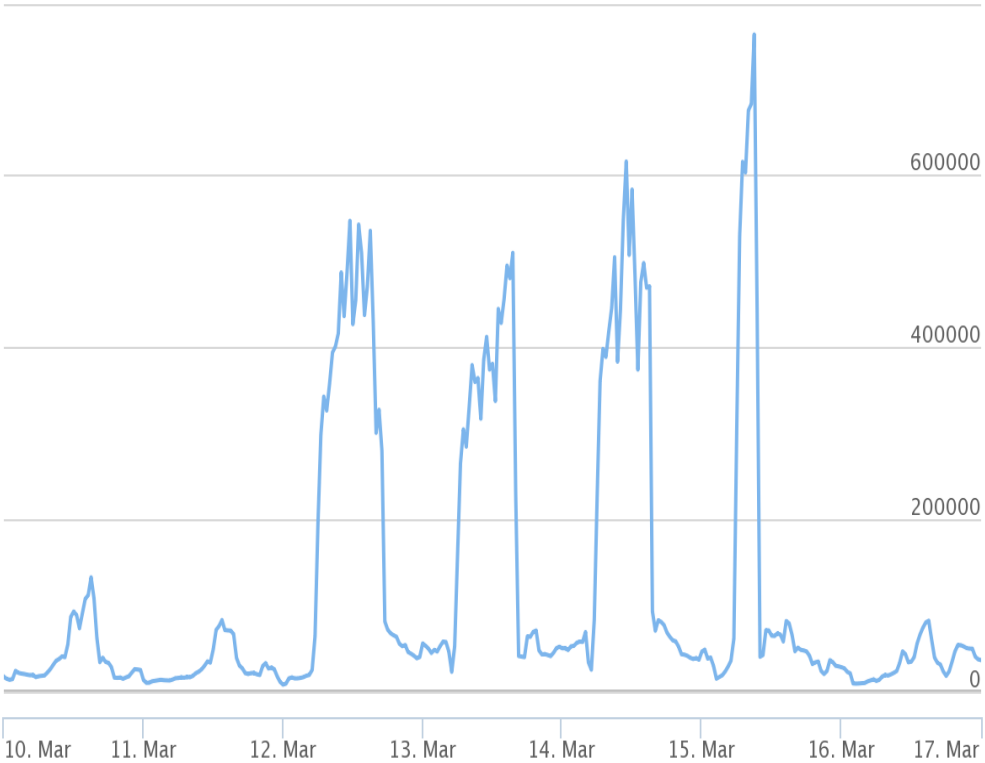


(c) Twitch esl_csgo Channel Viewers March 12-15, 2015

Figure 6.13: Twitch Viewers: ESL-One Katowice (March 12-15)



(a) Twitch Viewers March 10-17, 2015



(b) Twitch CS:GO Viewers March 10-17, 2015

Figure 6.14: Twitch Viewers March 10-17, 2015

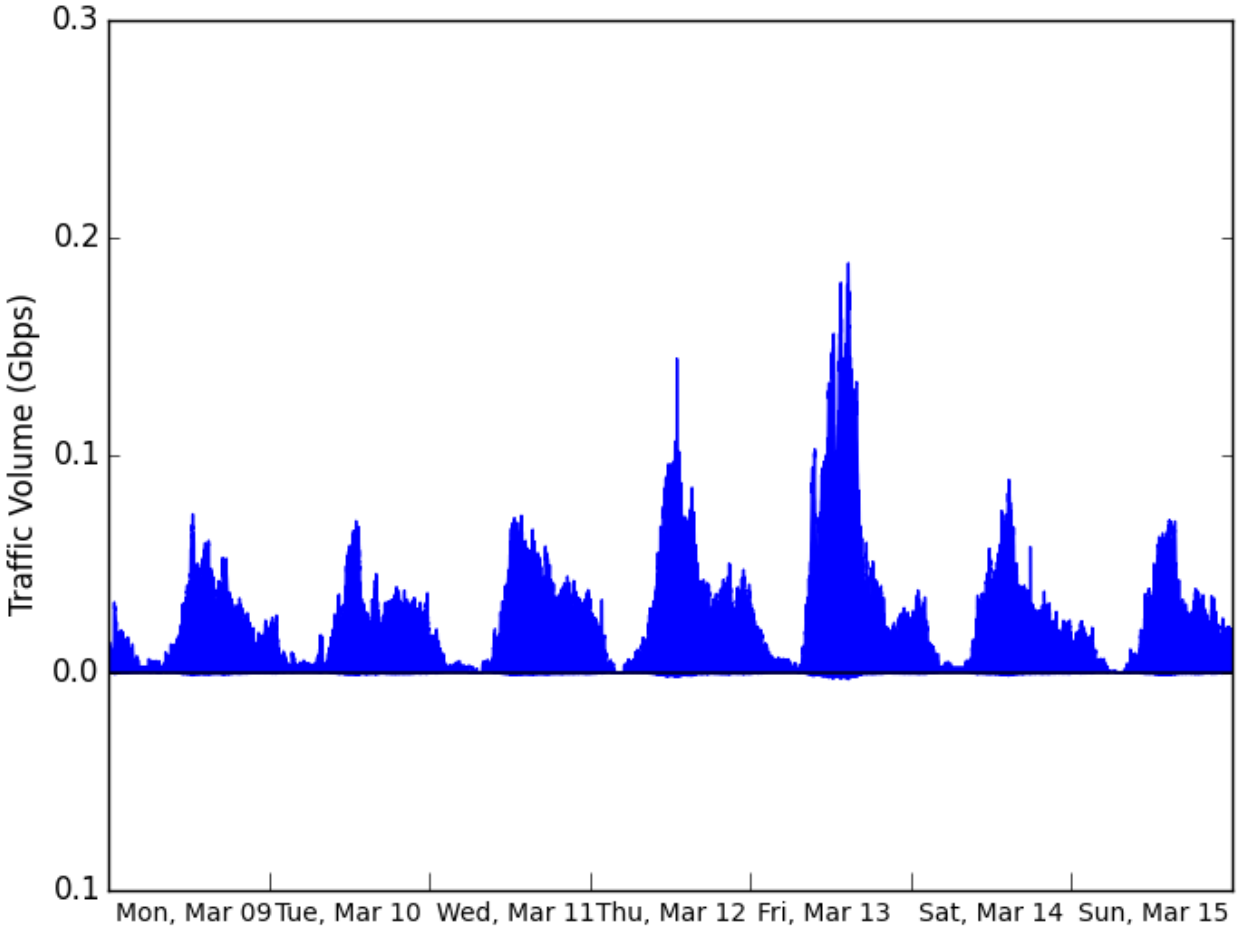


Figure 6.15: Twitch Traffic: March 9-15, 2015

Chapter 7

Conclusions

This chapter summarizes the observations made in the thesis. The thesis itself is summarized in Section 7.1. Overall NetFlix and Twitch measurements are presented in Sections 7.2 and 7.3, respectively. Conclusions are discussed in Section 7.4. Finally, future work in the area is summarized in Section 7.5.

7.1 Thesis Summary

This thesis presents an analysis of video traffic at the University of Calgary, focusing on NetFlix and Twitch. Our observation period ran from December 1, 2014 to April 29, 2015. In this study, we investigated how popular video services were used on campus. Our analysis was done with data taken from the edge of the University of Calgary's network. The results of this thesis show that video traffic is a dominant contributor to overall network traffic.

Chapter 1 introduced the thesis and presented our goals.

Chapter 2 presented background information on the TCP/IP stack and technologies used in media streaming. Modern video streaming is done over HTTP by a protocol called DASH (Dynamic Adaptive Streaming over HTTP). We described related work in the areas of network measurement and video traffic characterization. Finally, we introduced NetFlix and Twitch and summarized recent studies involving these services.

Chapter 3 described our collection capabilities and methodology. We listed the interruptions in our collection of data. We also presented a high level overview of campus traffic.

In Chapter 4, we presented aggregate video traffic measurements. We described the content types that are typically associated with video and their origins. We gave a brief overview of traffic levels associated with another popular video streaming service, YouTube,

and presented the high level trends of video streaming over our observation period.

Finally, in Chapters 5 and 6, we presented our analysis of NetFlix and Twitch, respectively. We summarize these chapters in greater details in the following sections.

7.2 NetFlix Characterization

In Chapter 5, we overviewed the traffic NetFlix sends to campus. We described the URIs NetFlix uses to transport content.

When viewing NetFlix, users have strong diurnal patterns, with peaks occurring in the afternoon and late in the night. The diurnal patterns that NetFlix (and other video services) display on campus may be different than what is observed in residential networks as the peak rates occur during work hours. We found that TCP connections used to transport content tend to be highly asymmetric, with an average of 370 KB sent to NetFlix, and 26 MB received over 160 seconds. This leads to multiple connections being used to transport content from NetFlix; we found 7-9 were used for a 22-minute episode and 12-14 for a 42-minute episode. We expect that NetFlix's use of DASH to serve video results in multiple connections. The request-response pairs that were sent showed different characteristics, depending on whether they were sent from desktop or mobile devices.

Finally, we were able to track what content was popular on NetFlix. Viewers had a strong preference to watch TV series such as *Friends*. However, some newly added content experienced short-term popularity on NetFlix. This characteristic was visible for both movies and TV-shows. When a new season of a TV show was added to NetFlix, such as *House of Cards* or *Daredevil*, the show had a brief surge in popularity as viewers consumed the new content and then returned to previous viewing habits. We estimate that caching popular shows on the local network will greatly reduce the amount of incoming traffic; i.e., it would only take around 70 GB of space to store *Friends*, and that show transmitted more than 20 TB to the campus network during the collection period. Due to licencing and DRM issues

however, operating our own cache is impossible. If network operators wanted to reduce this type of traffic they could offer to host a NetFlix CDN node on their network.

7.3 Twitch Characterization

In Chapter 6, we described Twitch's live-streaming.

Twitch uses Apple's HLS service as a base for their live-stream implementation. We found that HLS response sizes showed step-like behaviour due to the underlying (Apple HLS) technology. Response durations for HLS content tended to remain under one second; fast responses greatly contribute to a positive user experience.

When viewing connections, we found that they mirrored the characteristics of general video streaming, and were highly asymmetric. Since we did not see significant upload traffic to Twitch servers, we can assume that either no one on campus has attempted to stream video games during our collection period, or that the servers receiving a stream are different from the ones providing the stream to viewers. We have observed once again, that multiple connections are used to transport video and attribute this behaviour to DASH.

Twitch provides less content (in bytes) than NetFlix to viewers at the University of Calgary. Viewers consuming content from Twitch showed strong diurnal activity that stopped earlier in the night than other video services; we attribute this to the streamers going offline. This suggests that the more popular streamers viewed on Twitch are somewhere in North America.

The popularity of streamers and the volume they transmit was also examined, and we found that very few streamers have long-term popularity. Many of the popular streams in a given month are highly seasonal; they are popular because the stream is hosting an event and the stream is no longer viewed when the event is over. We were able to give a rough estimate of how much traffic volume could be saved if we were able to locally replicate Twitch streams. Since local replication would need TCP/IP multicasting, which is not widely supported, this

solution cannot currently be implemented.

Finally, we also presented a case study of an eSports tournament. We used data both from the campus network and from a third party that provided global information about Twitch. We found that users on campus do watch these types of events – when it is convenient for them; very few will adjust their schedules to watch the stream early in the morning.

7.4 Conclusions

Over our five-month observation period, we saw significant volumes of traffic to NetFlix and Twitch. Since NetFlix does not have a public API to gather and compare data, we could only state what is popular locally. Twitch, on the other hand, has an API that we can use to gather and compare data; we used information from the API when investigating an eSports tournament in March. Using the locally collected data, we found that these two services and YouTube provide a majority of the video traffic on campus, and thus a majority of the Web traffic that we see on campus.

Popular content from NetFlix tended to either be newly added content or TV shows with long-term popularity. We do not believe that this differs from global trends. Caching this content locally would greatly improve network utilization and user experience as well as resilience in face of flash crowds. NetFlix traffic levels were not greatly affected by user-generated activity (ratings and reviews). This is expected, as another study [11] (on other services) revealed that relatively few users provide feedback and that ratings were slightly more common than comments or reviews. On NetFlix, content ratings are sent via GET requests and reviews are done via POST requests.

While our measurements showed that Twitch generated less traffic than other services such as NetFlix and YouTube, Twitch generated significant levels of traffic over the observation period. A majority of Twitch's traffic was for live content. The availability of live content limits user consumption. The popular streams in each month are influenced

by events; i.e., streams associated with eSports gain a substantial amount of viewers when a tournament takes place. There is also a small set of streams on Twitch with long-term popularity, but the amount of traffic they contribute to total Twitch traffic does not have the same impact as the top NetFlix titles have on NetFlix's total traffic.

When measuring the connections and request-response pairs used to transport content from these services, we find that they do not greatly differ from the general characteristics of video traffic observed in other studies.

The findings of this thesis, issues we encountered, and the evolution of these services all provide the basis for future studies of video traffic.

7.5 Future Work

The work done in this thesis can be extended in multiple dimensions. More work understanding local user interaction with video services may be done. Identifying and characterizing sessions on these services will provide more insight on user-level interactions. We were not able to identify the number of sessions or viewers on campus for this thesis. Additionally, for NetFlix, we did not take into account user ratings or reviews. While ratings and reviews do not add a lot of traffic, we may find that users rating content "poor" may stop viewing part way through, as in other studies [58]. When studying Twitch, we did not measure chat levels or content. Measuring the contents of chat is a social study that was beyond the scope of this thesis. Another difficulty in measuring the content of chat is that it must be done on a room by room basis using the API (for authentication), to allow access to the IRC channels themselves.

General content level measurements can be improved for both of these services. NetFlix content measurements may be further improved by aggregating more of the individual episode IDs with the main content IDs. Work can be done with NetFlix in order to map request URIs to content (without the referrer URI). Our brief investigation of the request

URIs did not reveal a link between the requests and the content being transported. This has limited our understanding of mobile trends on NetFlix. More work can also be done measuring other eSports tournaments on Twitch. We chose to measure the largest tournament held during our collection period. We found that the tournament we chose to study was not very popular locally, yet it was extremely popular on Twitch.

Other researchers conducting similar studies in the future will face two challenges. First, both NetFlix and Twitch have recently changed aspects of their Web interfaces (briefly overviewed in the appendices). Changes to the interface are accompanied by different requests, which may also change response characteristics. Second, NetFlix has announced its intention to switch to HTTPS (video content is already transported over HTTPS). We expect that in the future Twitch will do the same. This will end the abilities of network researchers to study the application-level interactions of these services.

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Appendix A

UDP Traffic

Over our collection period, we observed over 990.2 TB of UDP traffic, with 866.4 TB (87.5% of UDP) outbound and the remaining 123.8 TB inbound. Non-standard ports were used to transmit 198.7 TB (20.1%) of all bytes. i.e., $n > 1,023$ where n was a port number involved with the connection. This traffic is likely BitTorrent traffic (explained below).

The two greatest contributors to outbound UDP traffic were NTP exploitation attacks (detailed later), and BitTorrent traffic. The volume of UDP traffic being used for legitimate purposes is negligible, since outbound NTP and BitTorrent[1] contributes 95% of all outbound bytes; NTP accounts for 73.7% of outbound UDP traffic, and those transmitted from non-standard ports account for over 22.9% of outgoing bytes.

Excluding connections that had non-standard values for both source and destination ports, and NTP connections (destination port number 123) [46], the largest contributors to outbound UDP traffic over our collection period were: 443 (HTTPS via QUIC[2] – 19.24 TB), 53 (DNS – 2.629 TB), 80 (HTTP via QUIC – 1.835 TB), and 19 (Character Generator Protocol (CHARGEN) – 1.386 TB). The other well-known services each sent less than 1 TB of UDP traffic over the collection period. These services include Simple Mail Transfer Protocol (SMTP) and Simple Network Management Protocol (SNMP), these services provide and manage Internet infrastructure.

Inbound UDP traffic, excluding NTP and non-standard ports, was primarily composed of the following protocols: 80 (HTTP via QUIC – 15.11 TB), 22 (SSH – 5.182 TB), 443 (HTTPS via QUIC – 2.808 TB), and 53 (DNS – 0.804 TB). All other well-known services accounted for less than 0.1 TB of inbound UDP traffic.

[1] A majority of BitTorrent volume is not attributed to legitimate filesharing.

[2] Quick UDP Internet Connections (QUIC)[69], is a protocol designed by Google for the Chromium project to improve the performance of Web applications.

A.1 NTP

For most of our collection period, we observed an on-going NTPv2 attack involving exploitable servers on campus. The attack is a well-known amplification attack[3,4] that has been discussed in a previous study by Czyz et al. [16]. Attackers utilizing this exploit send a small packet with the victim's IP address in the source IP field to a vulnerable server. The server will respond by sending the victim a larger response (a list with up to 600 responses to previous queries). By enticing enough responses of this type at once, the attacker is able to overwhelm the victim with massive amounts of data that clog up the victim's network.

On April 12, 2015, the outbound UDP traffic dropped significantly, almost ending the attacks; note the outbound UDP level in Figure 3.1 compared to 3.2. The NTP attacks generated over 638.8 TB of traffic during our observation period. See Table A.1 for a breakdown of the volumes involved in the attack.

Table A.1: Outbound NTP Traffic Volumes

	NTP Volume	Percent of Outbound UDP
December	143.2 TB	62.8%
January	215.7 TB	85.1%
February	89.14 TB	72.8%
March	112.2 TB	74.9%
April	78.60 TB	69.9%

Total volume: 638.8 TB

We shared this information with UCIT to assist in stopping the exploitation.

A.2 BitTorrent

BitTorrent is a popular peer-to-peer file sharing protocol. It may be implemented in either TCP or UDP (referred to as uTP). We only started to identify BitTorrent connections in mid-March. We tag a connection as a BitTorrent connection if both ports are ephemeral and the

[3] http://blog.cloudflare.com/understanding-and-mitigating-ntp-based-ddos-attacks/

[4] http://blog.cloudflare.com/technical-details-behind-a-400gbps-ntp-amplification-ddos-attack/

connection contains the string "BitTorrent protocol" in the payload. A consequence of this is that we are unable to detect encrypted BitTorrent connections, and we may unintentionally tag non-BitTorrent connections.

In April 2015, we observed 51.9 TB of UDP traffic on non-standard ports, constituting 36.8% of UDP traffic (141 TB). We tagged over 64 million UDP connections as BitTorrent, with a total volume of 23.2 TB (44.7% of non-standard UDP). Within this, 7.7 TB was inbound and 15.5 TB was outbound.

Appendix B

HTTP User Agents

We are able to use the user-agent attribute in Bro's HTTP logs to find what device/OS/browsers are preferred by users.

B.1 Total HTTP

Over our collection period, we observed 2.11 million variations of user-agent strings making over 10.5 billion requests. There are a total of 8.69 billion requests that we were able to parse into (OS, Browser) tuples. The remaining 1.81 billion that we could not parse are discussed in the Operating System subsection below. Tables B.1 and B.2 contain some summary statistics for user-agents (inbound and outbound).

B.1.1 Operating System

Table B.1 lists information for most Web browser options. The percentage listed with each item is out of total requests, not the 80% that were parsable. It shows that a majority of requests (50.5%) come from a browser that states it is running a Windows variant, with the most popular being Windows 7. Mac OS is the second most popular with 18.9% of requests. Mobile devices (iOS and Android) account for 11.35% of requests that we see.

There are over 1.81 billion requests (17.2%) from over 1.14 million user-agents that have not been listed in Table B.1 due to errors when parsing them. Out of these: 614 million requests (5.85% of total) have empty user-agent strings, 164 million (1.57% of total) give the user-agent string "Shockwave Flash", 111 million (1.05% of total) are from Red Hat's implementation of the `wget` program, and the rest of the requests are from other terminal user agents or, more commonly, bots.

Table B.1: HTTP User-Agent OS

OS	Version	Request Count	Percent
Windows	Total	5.3 billion	50.5%
	Windows 7	3.2 billion	31.8%
	Windows 8(.1)	1.3 billion	12.0%
	Windows XP	421 million	4.0%
	Windows NT	10.5 million	$< 0.01\%$
	Phone	4.7 million	$< 0.01\%$
	Other	285 million	2.7%
Macintosh	Total	2.0 billion	18.9%
	OS X 10.10.*	907 million	8.5%
	OS X 10.9.*	566 million	5.3%
	OS X 10.8.*	168 million	1.5%
	OS X 10.7.*	178 million	1.6%
	Other	217 million	2.0%
iOS	Total	792 million	7.5%
	iPhone	618 million	5.9%
	iPad	169 million	1.6%
Android	Total	400 million	3.8%
Linux	Total	198 million	1.9%
Other	Total	19.5 million	0.2%

There are also many user agents in the logs that are incorrect or malicious. We have detected 2,445 different "user-agents" that fall under this category. Out of these requests, 2,390 agent strings are associated with the ShellShock exploit; over 634,000 malicious requests were made over the observation period. The other 55 user-agent strings in this category were either completely mangled ("(X11;") or were part of an SQL injection attempt.

B.1.2 Browser

The most popular browsers (see Table B.2) were Chrome, Firefox, Internet Explorer, and Safari. This ordering is interesting since there are only 1.38 billion requests with Internet Explorer compared to 5.30 billion from a Windows machine. Chrome is the overall most-used browser (with 40.4% percent of requests). Firefox also has a significant presence with a similar number of requests as Internet Explorer. This shows that third-party browsers – at least on Windows machines – are used more than the default choice.

Table B.2: HTTP User-Agent Browser

Browser	Version	Count	Percent
Chrome	Total	3.5 billion	40.4%
	v40+	1.9 billion	21.9%
	v35-39	1.3 billion	15.4%
	Other	254 million	2.9%
	iOS	20.2 million	0.2%
Firefox	Total	1.4 billion	16.2%
	v35+	780 million	9.0%
	v30-34	472 million	5.3%
	v25-29	42.6 million	0.5%
	Other	117 million	1.4%
Internet Explorer	Total	1.4 billion	15.9%
	v10+	849 million	9.8%
	v7-9	498 million	5.7%
	v6	26.1 million	0.4%
	Other	8.4 million	$< 0.01\%$
Safari	Total	1.3 billion	15.0%
	v8	651 million	7.5%
	v7	393 million	4.5%
	v6	162 million	1.9%
	Other	95.2 million	1.1%
Other	Total	1.1 billion	12.5%
	Unknown	826 million	9.5%
	Opera	46.2 million	0.5%
	Other	213 million	2.5%

Percent is out of 8.69 billion

B.2 Video User-Agents

Out of the 160 million request-response pairs for video content, over 148 million requests (92.8%) had parseable user agent strings. Among the 11.5 million requests (7.20%) that could not be parsed, 5.66 million requests (3.54% of total) had empty user-agent strings. A breakdown of parseable strings is shown in Table B.3.

The user-agent string patterns for desktop OSs (Windows and Macintosh) mirror general usage described previously.

For mobile devices, however, we find different usage patterns. When viewing video on mobile devices, users often use an App to do so; this leads to "Unknown Browser" strings

Table B.3: Video User-Agents

OS	Browser	Requests	Percent	Volume
Windows	Total	86.3 million	54.0%	70.03 TB
	Chrome	47.2 million	29.5%	45.91 TB
	Firefox	18.0 million	11.3%	12.25 TB
	IE	19.4 million	12.1%	7.94 TB
	Other	1.7 million	1.1%	3.93 TB
Macintosh	Total	30.6 million	19.2%	34.46 TB
	Chrome	9.3 million	5.8%	13.43 TB
	Safari	17.5 million	11.0%	12.24 TB
	Firefox	3.0 million	1.9%	2.85 TB
	Other	0.8 million	0.5%	5.94 TB
iOS	Total	24.3 million	15.2%	23.90 TB
	Safari	3.5 million	2.2%	5.67 TB
	Unknown	20.8 million	13.0%	18.23 TB
Android	Total	4.5 million	2.8%	6.94 TB
	AndroidBrowser	3.8 million	2.4%	5.78 TB
	Chrome	0.7 million	0.4%	1.23 TB
	Other	12,000	$> 0.01\%$	52.71 GB
Other	Total	2.7 million	1.7%	4.17 TB
Unknown	Total		7.1%	

when trying to parse iOS browsers, and 'AndroidBrowser' appearing when trying to parse browsers from Android devices.

B.2.1 Flash User Agents

Flash content was most frequently retrieved by user-agents of type "Shockwave Flash", with 164 million requests (62.0% of Flash requests). No user-agent was given for 19.3 million (7.30%) of Flash requests.

B.3 NetFlix User Agents

Table B.4 shows the user agents observed for NetFlix traffic. There are some major differences from the previous user-agent trends. First, we find that Macintosh is the most-used OS. We also see that in Windows systems, the ordering of Firefox and Internet Explorer has also

Table B.4: NetFlix User Agents

OS	Browser	Count	Percent
Macintosh	Total	108 million	35.5%
	Safari	53.8 million	17.6%
	Chrome	46.2 million	15.1%
	Firefox	6.1 million	2.0%
	other	2.3 million	0.8%
Windows	Total	75.4 million	24.6%
	Chrome	56.1 million	18.3%
	IE	8.3 million	2.8%
	Firefox	10.9 million	3.5%
	other	4,607	$< 0.01\%$
iOS	Total	37.2 million	12.2%
	netflix-ios-app	1.4 million	0.4%
	IPad	21.8 million	7.2%
	iPhone	14.1 million	4.6%
Android	Total	4,486	$> 0.01\%$
Other	Total	84.4 million	27.7%
	Empty	81.9 million	26.9%
	unparseable	1.1 million	0.3%
	Linux	0.9 million	0.3%
	ChromeOS	0.5 million	0.2%
	other	100	$< 0.01\%$

changed, but Chrome still remains the most-used Windows browser. Finally, we see that the number of requests made from Android devices is extremely low.

There are multiple explanations for these observations. First, since the University does not provide as many MacOS workstations as Windows workstations, and since NetFlix is used for entertainment, we can assume that users are viewing NetFlix on their own devices instead of from University machines. The lower usage of Internet Explorer may also follow a similar explanation; when watching NetFlix on campus, a viewer will prefer to watch on their own device with their browser of choice. Finally, the low number of requests from Android devices is easily explained: we tested the NetFlix app on an Android device and found that no user-agent is attached to content requests so the user-agent field in the Bro log is empty.

B.4 Twitch User Agents

The user-agent strings used to view live-stream content are shown in Table B.5. Out of all user agent strings, 27 could not be parsed; they accounted for 0.17% of requests.

Table B.5: Twitch User Agents

OS	Browser	Count	Percent
Windows	Total	33.7 million	76.4%
	Chrome	29.3 million	66.7%
	Firefox	3.4 million	7.7%
	IE	0.7 million	1.5%
	Other	0.3 million	0.5%
Macintosh	Total	3.9 million	8.8%
	Chrome	2.2 million	5.1%
	Safari	0.9 million	2.1%
	Firefox	0.6 million	1.3%
	Other	0.1 million	0.3%
iOS	Total	2.5 million	5.6%
	iPhone	1.7 million	3.8%
	IPad	0.8 million	1.8%
Other	Total	4.0 million	9.2%
	Android	2.2 million	5.0%
	Linux	1.7 million	3.8%
	Other	0.1 million	0.4%

As Table B.5 shows, most users use Chrome on Windows when accessing Twitch from campus. Windows is once again the most used OS, as with viewing video content in general. Chrome is the most-used browser across all desktops when accessing Twitch. The table shows that mobile devices account for only 10% of requests.

Appendix C

NetFlix User Interface

The structure of a typical NetFlix session (on a desktop device) is as follows[1]. Upon visiting `http://www.netflix.com` for the first time, NetFlix responds with a HTTP redirect (301) towards `https://www.netflix.com`. It uses another redirect that handles geo-restrictions. In Canada, users receive a 302 redirect pointing them to `https://www.netflix.com/ca`. Next, NetFlix handles login authentication over HTTPS. After logging in through HTTPS, NetFlix reverts back to unencrypted HTTP for communication.

After logging in, the client requests NetFlix over HTTP and is redirected to `http://www.netflix.com/WiHome` to select the user's profile. Once the profile is selected, a second request to `/WiHome` is made and is successfully returned. The request path WiHome is short for Web Interface home. On the homepage for the Web interface, there is a menu with content that NetFlix suggests for the user, including a list of new (to NetFlix) content, content the user has not finished watching, and content similar to previously watched content (Figure C.1 provides a screenshot).

On selection of an item, the browser sends a request to `www.netflix.com/WiPlayer?movieid=<id>...` that results in a JavaScript player being loaded. Content is then transported with a different set of requests as outlined in Section 5.1. Figure C.4 provides an illustration of the session. Other domains involved when visiting NetFlix include CDNs operated by NetFlix and by third parties to load thumbnail images (i.e., movie/series covers as well as still frames from playing content).

A screenshot of the Web Interface player is visible in Figure C.2. Here we see the options for playing the content (pausing, tracking to a point of the video, skipping episodes, etc.)

[1]The sessions and request paths detailed in this thesis were valid during our collection period. In June 2015, NetFlix switched the desktop Web interface to use different paths.

Figure C.1: Screenshot of NetFlix Web Interface Homepage

on the bottom. On the right side of this bar (from left to right) there are options to skip to the next episode, list episodes (discussed in Section 5.2), captioning and language options, and finally a full screen mode option. If the user does not move their mouse cursor, this navigation bar disappears after a few seconds.

In Figure C.1, the cursor is hovering over an item *Sense8*. If the title for this item is selected, the user will be taken to a page similar to Figure C.3. The series page is the only way to transmit an episode's ID at the network level; autoplaying episodes or selecting from within the player adds the ID to the URI as a fragment.

Figure C.2: Screenshot of NetFlix Web Player

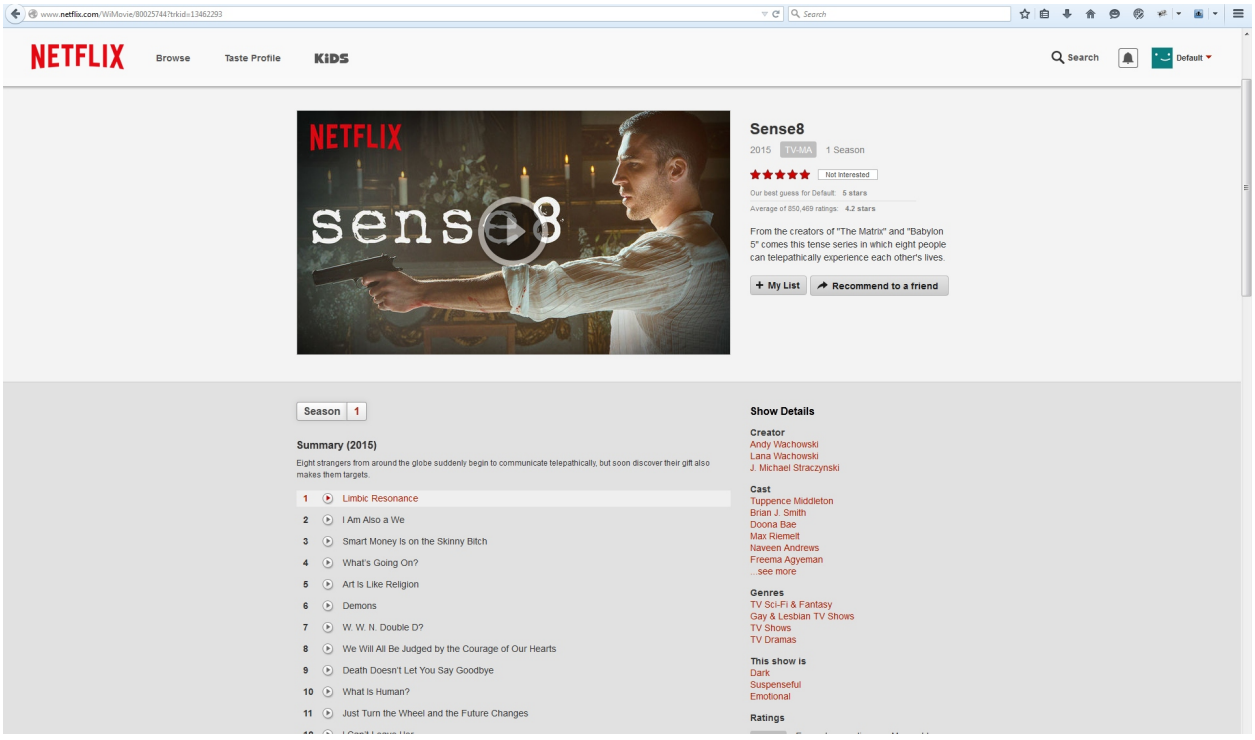


Figure C.3: Screenshot of NetFlix *Sense8* series page

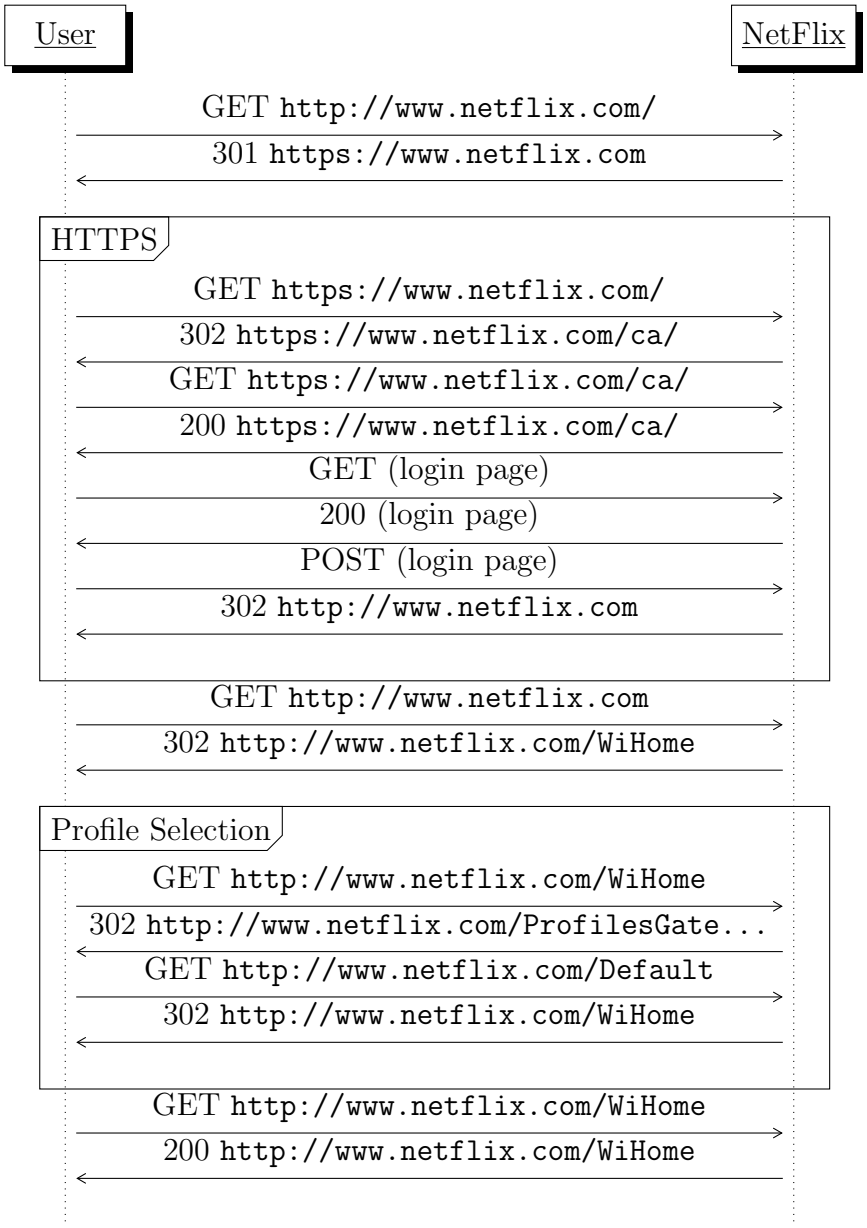


Figure C.4: A typical NetFlix session for a Canadian user, from login to browsing.

Appendix D

NetFlix IP range

During the collection period, the CIDR subnets that we found NetFlix traffic being transmitted from are as follows:

- 108.175.32.0/20
- 198.45.48.0/20
- 198.38.96.0/19
- 23.246.0.0/18
- 192.173.64.0/18

The following IP ranges are listed as associated with NetFlix, but we have not found that they transmitted any traffic of interest:

- 45.57.0.0/17
- 64.120.128.0/17
- 66.197.128.0/17

These IP addresses may be involved in serving other regions of the world, i.e., Europe or South America.

Appendix E

New NetFlix Paths

E.1 Login

In June 2015, NetFlix updated their desktop Web Interface. The new interface uses a different request structure that is outlined in Figure E.1.

In the new interface, a GET request is sent with profile information as parameters.

E.2 Content Viewing

When viewing content from NetFlix, the initial GET request from a desktop device is now directed towards a URI with the schema:

`http://www.netflix.com/watch/<ID>?trackId=...&tctx=...`

The ID in this case is the ID_e value when viewing a show. It seems that the previous ID_m values are used when viewing details about a show from the catalogue.

Additionally, some requests for content from the desktop are now transmitted over HTTPS. They seem to come from hosts that conform to the following naming scheme:

`https://ipv4_<X>.<Y>.ix.nflxvideo.net/range/<#>-<#>?o=...`

The IP addresses for these servers are the same as the ones described in Appendix D. As of July 27, 2015, mobile requests from Android devices remain unchanged.

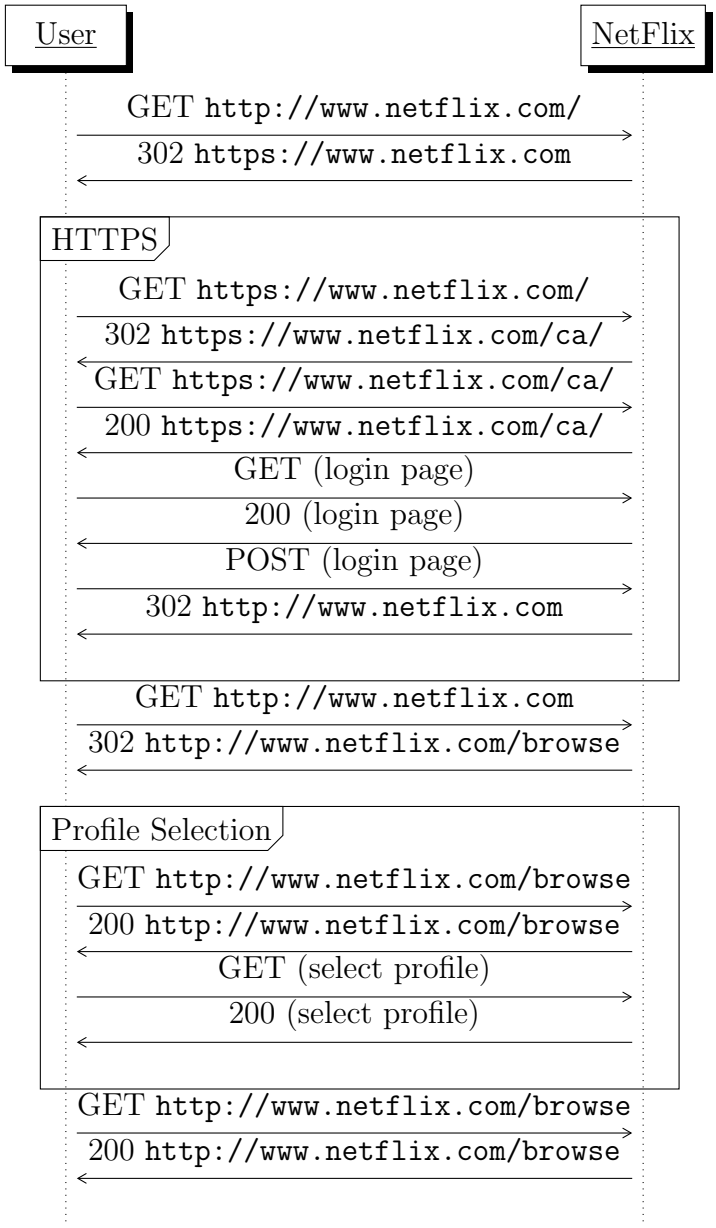


Figure E.1: New NetFlix paths, from login to browsing

Appendix F

Twitch Subscriptions and Partnership

A user on Twitch may subscribe for $8.99 a month to Twitch Turbo. This service gives multiple benefits to the user: no ads on streams, a customizable emoticon set for use in chat, a badge that appears beside your name in chat, extra colours for chat, and longer-term broadcast storage for VOD content of 60 days as opposed to the non-turbo limit of 14 days (for full broadcasts only, since highlights may be stored indefinitely).

Streamers who are popular on Twitch, or who have a large following for video game content (or may otherwise be considered a professional gamer), may apply for partnership with the site. Partnership offers several benefits to the streamer. The primary benefit is that it allows the streamer monetization options. The primary mode of monetization is allowing viewers to pay for subscriptions to a streamer ($4.99/month split between Twitch and the streamer). This subscription does not always offer the same benefits as the Turbo subscription. Another option is that Twitch allows the streamer to take donations (or tips) from the users on their channel. The minimum donation amount is $1.00[1]. Partnered streamers may be able to play ads (i.e., mid-roll commercial ads), for additional monetization. Streamers may promote other channels for monetization, such as selling merchandise on their channels. Top streamers on Twitch (and YouTube) can make millions of dollars a year [27]. Other features that a partnered streamer gains include 60-day VOD storage limit, better video transcoding options for viewers, delaying their stream by up to 15 minutes[2], and access to beta-test new features.

In return for subscribing to a channel, a user is often granted some privileges by Twitch and the streamer. Some examples of these privileges include usage of custom emoticons for

[1] In local currency.

[2] This delay is useful for multi-player games since it prevents viewers from influencing the outcome.

chat uploaded by the streamer, invitations to multi-player games with the streamer (the streamer can access their subscriber list to disseminate needed information), chat badges, and unthrottled chat usage (if a stream has a lot of viewers, chat may be set to a slow-mode or a subscriber-only mode). Subscription benefits are listed per streamer (multi-player invitations don't count as a benefit in this case, since Twitch cannot enforce it).

Appendix G

Twitch User Interface

Figure G.1 shows a screenshot of the Twitch homepage. There is an embedded stream in the centre of the page showcasing one of the featured streams, with a brief description of the stream to the right. Directly below the stream, there is a short icon list of featured streams, with the selected one highlighted (in this case, it is the one in the centre). Below the featured streams is a list of featured games. This list shows the box-art of the game, the title, and lists how many people are currently viewing the game. If the user were to scroll down on the homepage, they would see more featured games than top channel lists. Across the top of the page, from left to right, there is a link back to the homepage (the text 'Twitch'), a search bar, a link to browse Twitch's directory, a link to subscribe to Twitch Turbo, followed by the user's account setting and following list (or options to log in or register if you are not logged in).

Figure G.2 shows the page when a specific stream is being viewed. The request path when accessing the page is just the username. For the example, the URL is `www.twitch.tv/ddrjake`. On the left side are options to browse Twitch and access user settings. The top of the page has information about the stream itself. The streamer's avatar picture is on the right, followed by the title, streamer, and game being played. In this case, the title of the stream is "African Power as Loango" being broadcast by the streamer "DDRJake". The game being played is *Europa Universais IV*. Directly below the stream, from left to right, are options to follow the streamer, subscribe to the streamer (if they are a Twitch partner), a link to share the stream, a link to bookmark the stream, a theatre-mode option, followed by options to message the streamer or report the stream. Below these options, there is a full description of the streamer (that they upload themselves). On the right side of the page is

Twitch Chat, described in Section G.2.

The Twitch Player itself uses Flash[1] to handle user interaction.

If a user chooses to subscribe to a streamer, they are taken to a page similar to Figure G.3. This page lists the streamer that you are subscribing to on the left, as well as any benefits granted. To the right side of this are the payment options; the subscribe page, and any payment pages, are transmitted via HTTPS.

If a user is logged in and selects their following page, they see a page similar to Figure G.4. This page has the same options as there were in Figure G.2 on the left side of the page. In the centre of the page, there is a list of all live-streams that have been followed. The top row shows live-streams, and below is a list of all streamers hosting a stream (described in sub-section 6.1.1). Along the bottom of the page is a list of recent broadcasts (VOD content).

G.1 Twitch Domains

We have observed Twitch video content originating from two different domains owned by Twitch: `twitch.tv` and `ttvnw.net`. From December 1st, 2014 through March 16th, 2015, video traffic was mostly delivered by `twitch.tv`, but from March 16th until the end of our collection period in April 2015, `ttvnw.net` was used. Other domains owned by Twitch, such as `jtvnw.net` and `justin.tv`, are used by Twitch to deliver other elements, such as static documents. Additionally, `jtvnw.net` has a CDN domain for serving images for Twitch. Almost all video content from Twitch (from `twitch.tv` or `ttvnw.net`) comes from servers running Apple's HTTP Live-Streaming (HLS) service. HLS is an implementation of the DASH protocol.

[1] As of July 22, 2015, Twitch has started to use an HTML5-based video player with underlying Flash content. They are planning on upgrading to a full HTML5-based solution soon.

G.2 Twitch Chat

Twitch provides a chat functionality so that viewers may converse with the streamer or with each other. The chat is actually a Web interface to an Internet Relay Chat (IRC) channel. Twitch previously used Flash on the end-user's device to handle the chat functionality, but as of July 1, 2015, they have switched to using a native HTML5 solution.

On the right side of Figure G.2 is the chat panel of Twitch. Only viewers who have logged into an account with Twitch may participate in the chat. Additionally, the chat may be restricted to a mode, such as subscriber only. In this mode, only viewers who have subscribed to the streamer may contribute to the chat, but everyone may see the chat. On the left side of the user name, there may be a small icon, referred to as a 'badge'. A badge can indicate whether someone in chat is a subscriber to the streamer (stream specific icon) or Twitch Turbo (a battery icon), a chat moderator (a sword icon), or the streamer.

At a network level, we are unable to monitor application-level data from the chat sessions since secure WebSocket connections are used. Bro does not tag WebSockets connections by default, adding to the difficulties in identifying connections. The information that we get is basic since it only includes network-level details, such as connection duration, bytes transferred, and packets transferred. We chose not to present a breakdown of Twitch chat connections since they are more social in nature, and are out of the scope of this thesis. Other studies [28, 48] have previously detailed the social aspects of Twitch.

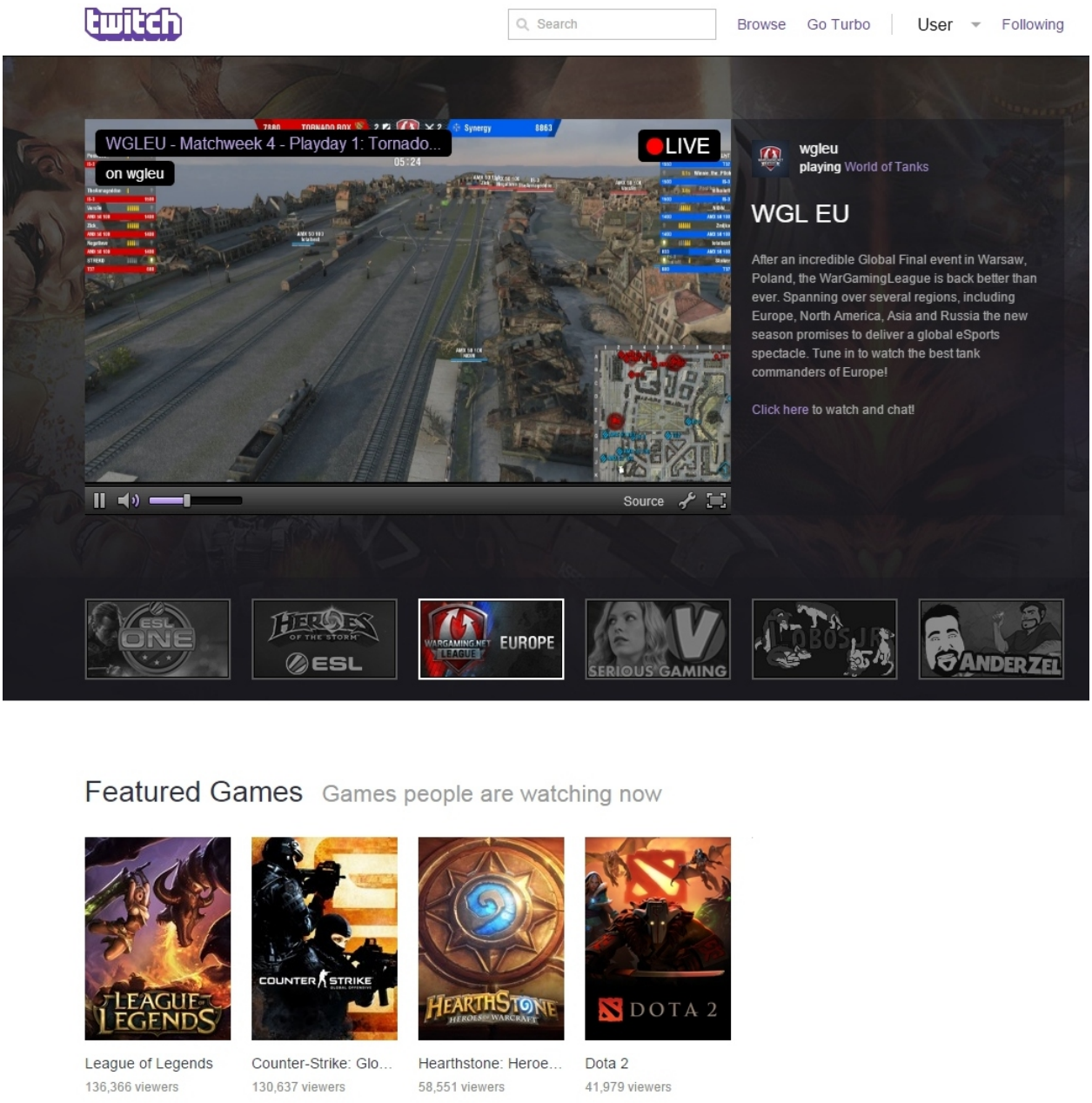


Figure G.1: Screenshot of the Twitch Homepage

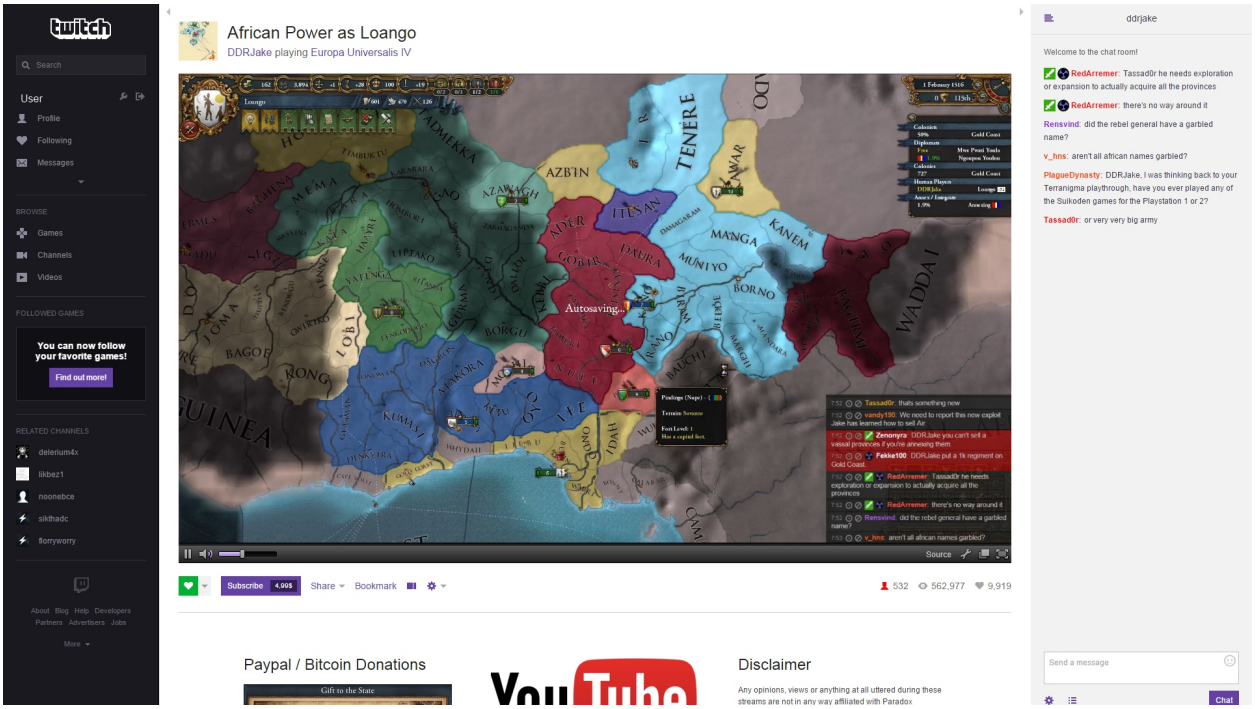


Figure G.2: Screenshot of a Twitch stream

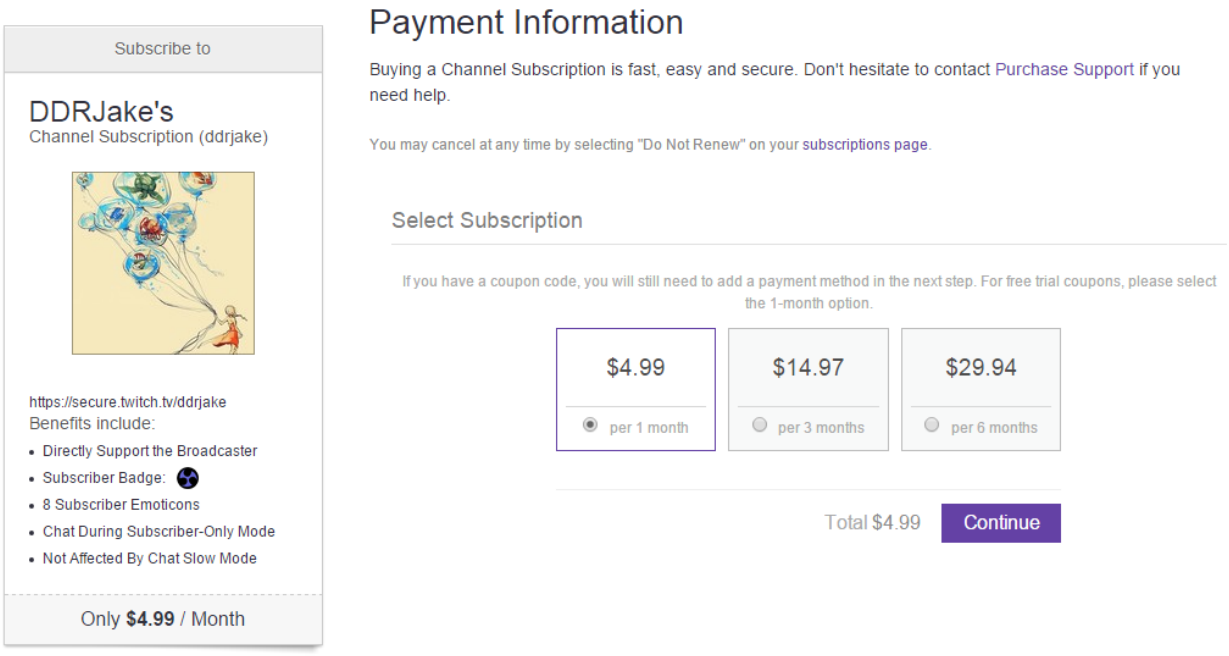


Figure G.3: Screenshot of a Twitch Subscribe page

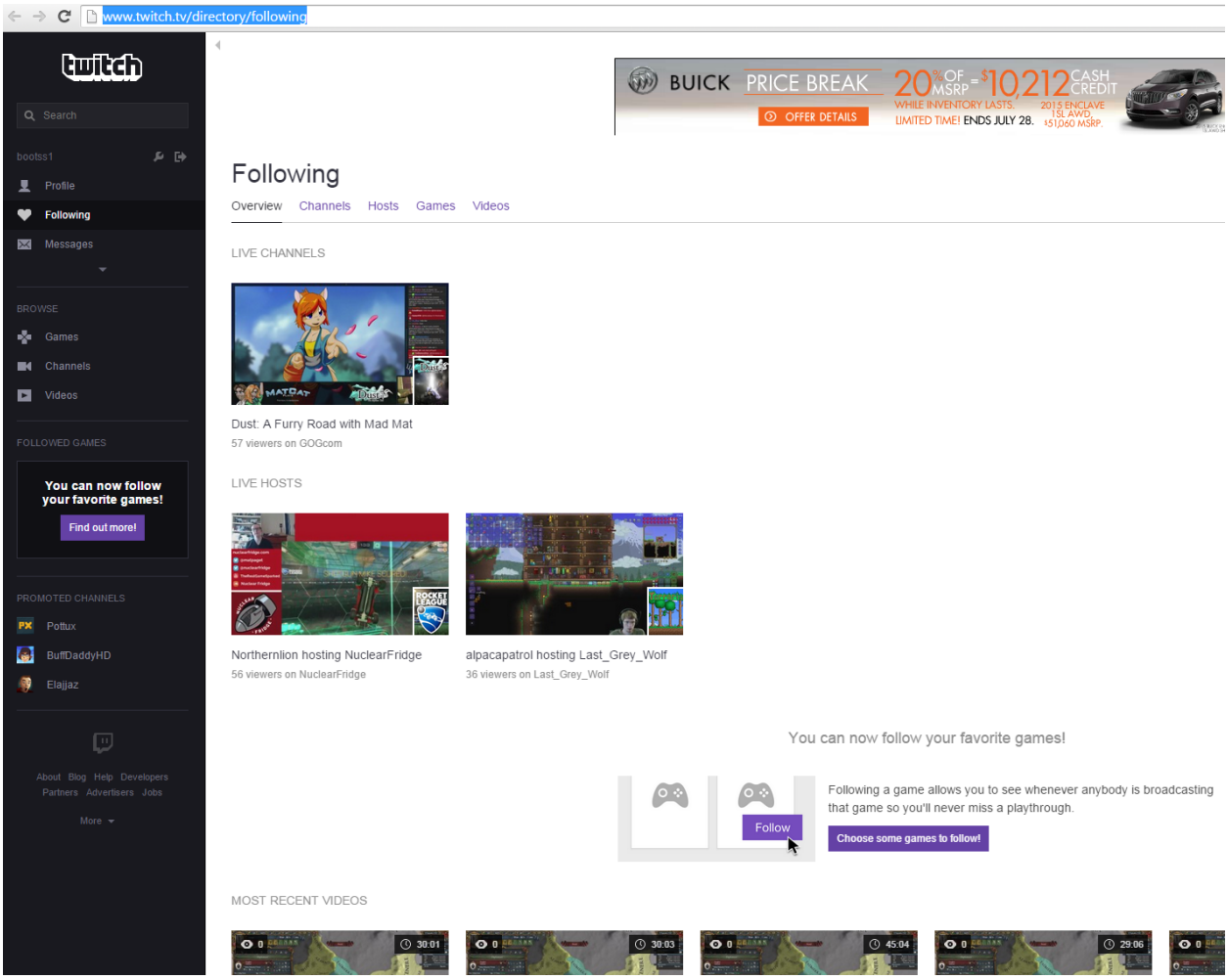


Figure G.4: Screenshot of a Twitch Following Page

Appendix H

Twitch Video on Demand

Twitch's Video on Demand (VOD) content comes in two forms. The more common one is pre-recorded HLS (`Video/mp2t`) content, that we describe here, and the other less common type is previous Flash content, which we discuss in Section H.1. The page for viewing VOD content on Twitch looks similar to the page in Figure G.2. The differences are the chat panel is replaced by a list of chronologically ordered VOD content by the streamer, and there is an option to skip to any position of the stream.

The host that serves HLS content for Twitch is named "`vod.ak.hls.ttvnw.tv`". A total of 465 GB of VOD traffic was observed coming from this host during our collection period. We have also observed just over 3 GB of video content from `vod.edgecast.hls.twitch.tv`; EdgeCast is Verizon's CDN service. The 'ak' part of the hostname seems to be static, and may indicate a link to the Akamai CDN (due to another CDN being identified in the same position). The request paths for VOD content conform to the following schema:

```
/v1/AUTH_system/vods_<i>/<streamer>_<l>_<m>/<quality>/index_<N>_<H>.ts?...
```

At the start of the request path is what appears to be a version indicator. The i value looks like a hexadecimal number that does not change for the individual VOD requested. The values l and m are the same values as for live-stream requests. That is, these values are determined on the original broadcast and reused for VOD access. The N and H values are the same for each request made to the VOD content. N is one of the n values from the live broadcast, and determines the start of the VOD section (a live broadcast may be broken into multiple VOD files). H is the hash value for the n value of the original broadcast. The query string following the URL specifies two numbers: start_offset and end_offset. These numbers request a specific part of the file from the server. For example, if request I has a start_offset

of 1 and an end_offset of 9, then request $I + 1$ has a start_offset of 10 and an end_offset of 18.

Additionally, when making a request to HLS VOD content on desktop devices, the request contains the following referrer:

`http://www.twitch.tv/<streamer>/v/<p>`

The value p is a number that is not related to any of the previous values. The value does, however, appear to be unique to the broadcast being requested.

Table H.1: Video On Demand (HLS) Content Volumes

	Volume	Connection Count
December	40.7 GB	30,349
January	82.3 GB	59,758
February	93.2 GB	72,109
March	124.0 GB	107,109
April	125.0 GB	114,109

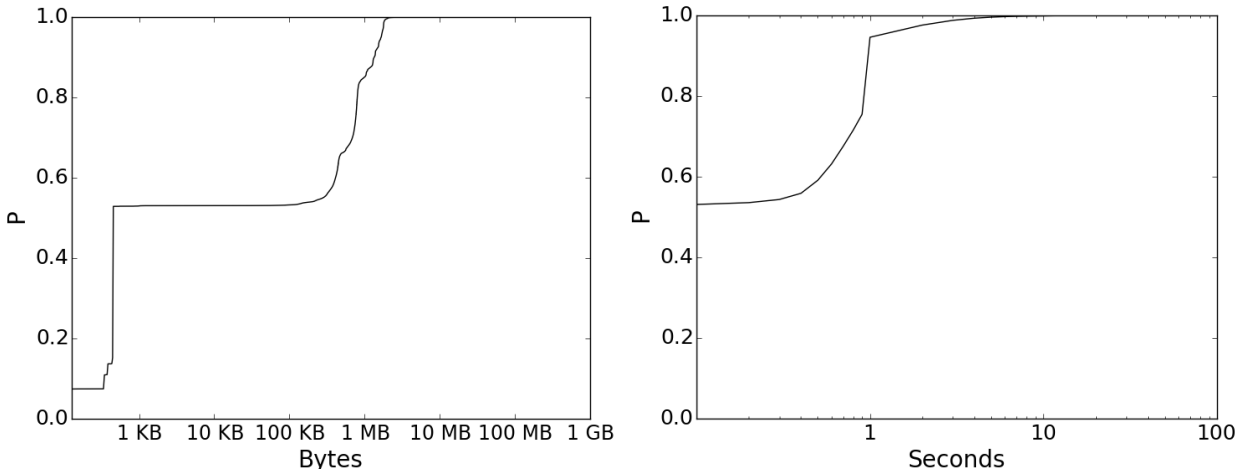
The volumes for HLS VOD content appear in Table H.1. The overall levels for VOD content are pretty low. This implies that most users on Twitch view live content. It is also important to remember that a streamer on Twitch may upload VOD content to another service. Twitch allows for easy upload to YouTube, for example.

Figures H.1a and H.1b show the CDFs for VOD response size and duration, respectively. These figures show the same behaviour as HLS (Figures 6.3b and 6.3a). The results are unsurprising since the same underlying technology, Apple HLS, is used for both.

H.1 Flash Videos

Some of the older VOD content from Twitch is served as Flash content. The host that serves this content is `media-cdn.twitch.tv`. The paths requesting Flash VOD content follow the format:

`/store<i>.media<j>/archives/<Date>/live_user_<streamer>_<k>.flv`



(a) Size CDF (b) Duration CDF

Figure H.1: Twitch VOD Response Characteristics

The i, j, and k values are numbers that do not appear to be related. Date is the date of the broadcast stream. The referrer for Flash VOD content is almost the same as the one used for HLS VOD content:

`http://www.twitch.tv/<streamer>/c/<p>`

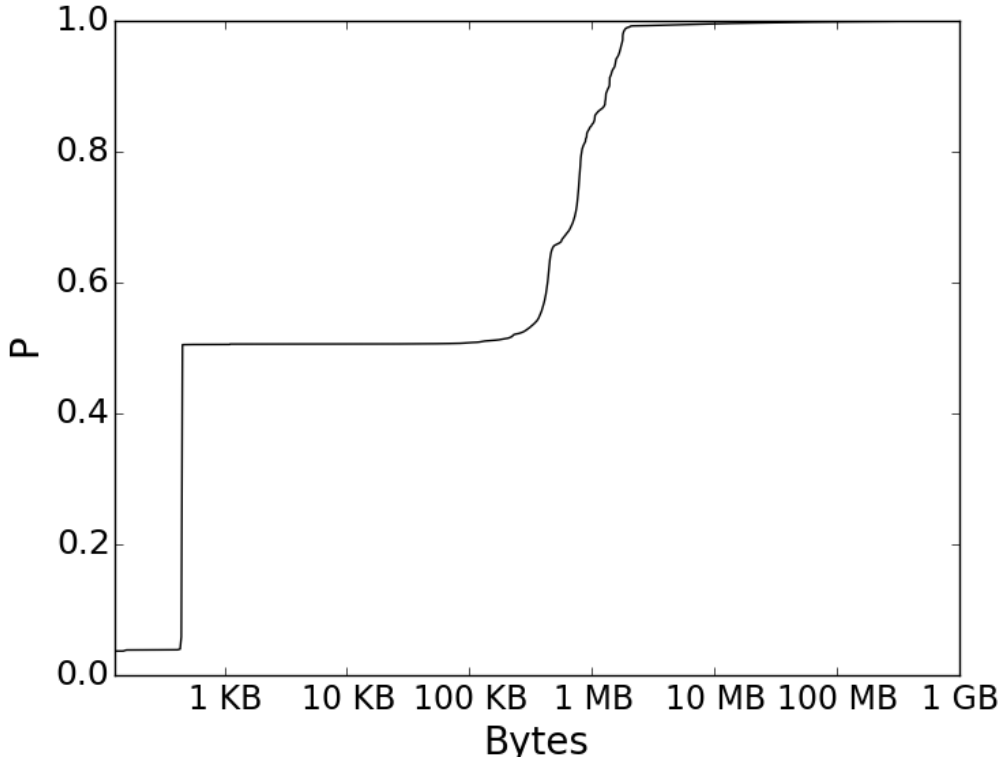
Once more, the p number does not appear to be related to any of the previous values.

Table H.2: Twitch FLV Content Summary

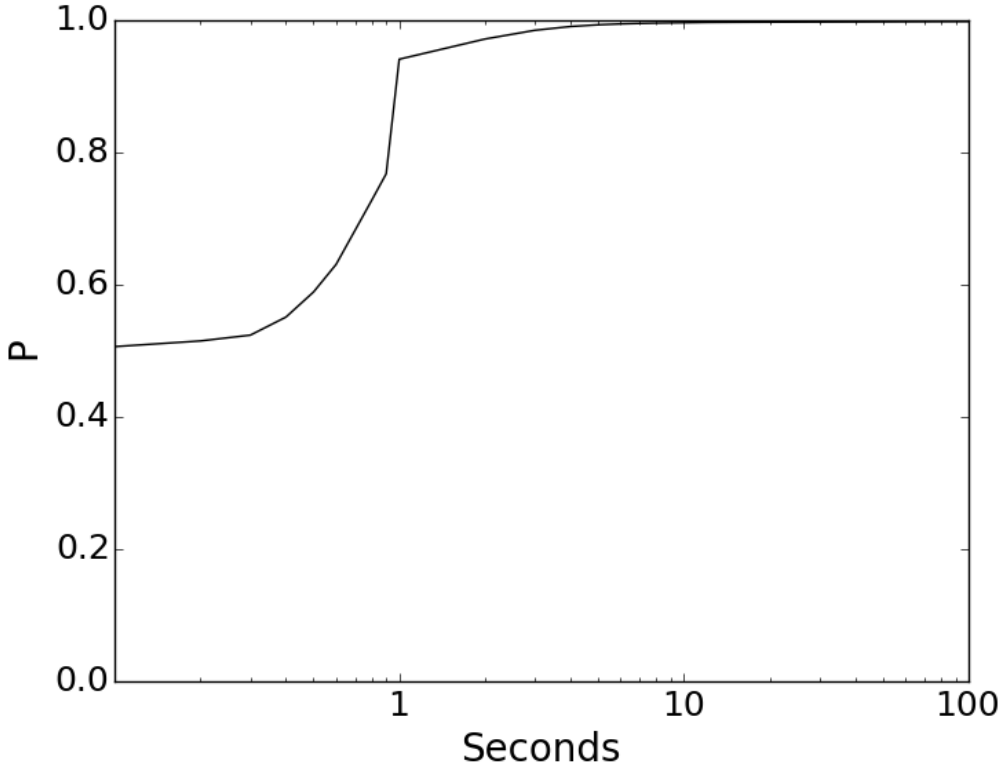
	Total Connections	Total Volume	Total Requests	Avg. Duration
December	2,932	185.2 GB	3,059	67.7
January	2,611	214.0 GB	2,712	165.0
February	1,815	135.1 GB	1,892	155.0
March	1,908	100.3 GB	2,021	125.0
April	1,607	84.4 GB	1,668	97.3

Table H.2 shows the summary statistics for Flash VOD content over the observation period. It clearly shows that VOD content delivered with Flash decreased over time.

Figure H.2a shows the response size CDF for Flash responses. There is a sharp increase of responses that have a length less than 512 bytes (between 460-470 bytes). Figure H.2b is the response duration CDF; it shows that most Flash responses take less than a second.



(a) Size CDF



(b) Duration CDF

Figure H.2: Twitch Flash Response Characteristics