10-year Experience of Internet Traffic Monitoring with Tstat

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***Abstract*—Network monitoring has always played a key role in understanding telecommunication networks since the pioneering time of the Internet. Today, monitoring traffic has become a key element to characterize network usage and users' activities, to understand how complex applications work, to identify anomalous or malicious behaviors. In this paper, we present our experience in engineering and deploying Tstat, a free open source passive monitoring tool that has been developed in the past ten years. Started as a scalable tool to continuously monitor packets that flow on a link, Tstat has evolved into a complex application that gives to network researchers and operators the possibility to derive extended and complex measurements via advanced traffic classifiers. After discussing Tstat capabilities and internal design, we present some examples of measurements collected deploying Tstat at the edge of several ISP networks in the past years. We then discuss the scalability issues that software based tools have to cope with when deployed in real networks, showing the importance of properly identifying bottlenecks.**

I. Introduction

Since the Internet childhood, network monitoring has played a vital role in network management, performance analysis and diagnosis. Nowadays, with the increased complexity of the Internet infrastructure, the applications and services, this role has become more crucial than ever. Over the years, a number of methodologies and tools have been engineered to assist the daily routines of traffic monitoring and diagnosis and to understand the network performance and users' behavior [1].

To analyze a system, researchers can follow experimental science principles and devise controlled experiments to induce and measure cause-effect relationships, or, observational science principles and, avoiding artificial interference, study the unperturbed system. In the specific field of network traffic measurement, the above two disciplines are referred to as *active* and *passive* measurements, respectively. The active approach aims at interfering with the network to induce a measurable effect, which is the goal of the measurement itself. Active approaches generate traffic, e.g, by injecting specifically crafted probe packets or alter the network state, e.g., by enforcing artificial packet loss. A number of Internet monitoring tools are based on active probing, ranging from simple operation management or network tomography via "ping" or "traceroute", to more complex delay and capacity estimation via "capprobe" or "pathchar". Finally, large and controlled testbeds can be easily setup using tools like "netem" or "dummynet". For the passive approach pure observations are performed by means of dedicated tools, named "sniffers" by the Internet metrology community, that simply observe and analyze the traffic that flows on links. Several passive measurement tools are available. Some tools, such as "tcpdump" or "Wireshark", are designed to let researchers interactively analyze the captured packets. Other tools are instead automated, so that the human interaction is minimized; examples are the flow-level monitoring tool "NetFlow", intrusion detection system like "Snort" or "Bro", and the traffic classification tool "CoralReef". A comprehensive list of both active and passive tools can be found in [1].

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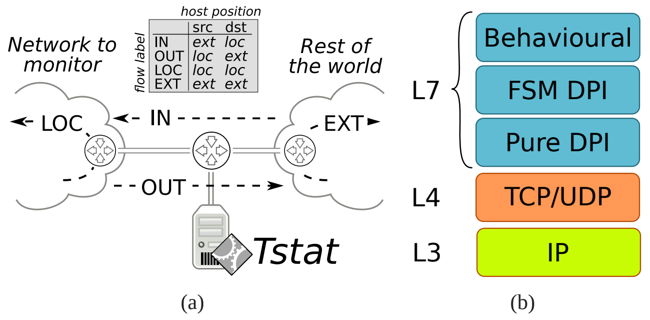


Fig. 1. Tstat monitoring probe setup (a) and analysis workflow (b).

Tstat is an example of automated tool for passive monitoring. It has been developed by the networking research group at Politecnico di Torino since 2000 [2]. Tstat offers live and scalable traffic monitoring up to Gb/s using off-the-shelf hardware. It implements traffic classification capabilities, including advanced behavioral classifiers [3], while offering at the same time performance characterization capabilities of both network usage and users' activities [4]. After more than ten years of development, Tstat has become a versatile and scalable application, used by several researchers and network operators worldwide. In this paper, we report our experience with Tstat development and use. We illustrate as a case study the traffic evolution as observed during the last year at different vantage points in Europe, and discuss some issues about the feasibility of Internet traffic monitoring with common PCs that can help researchers to avoid common pitfalls that we have faced in the past.

II. Tstat overview

Tstat started as evolution of *tcptrace*[5], which was developed to track and analyze individual TCP flows, offering detailed statistics about each flow. Tstat initial design objective was to automate the collection of TCP statistics of traffic aggregate, adding real time traffic monitoring features. Over the years, Tstat evolved into a more complex tool offering rich statistics and functions. Developed in ANSI C for efficiency purposes, Tstat is today an Open Source tool that allows sophisticated multi-Gigabit per second traffic analysis to be run live using common hardware. Tstat design is highly flexible, with several plugin modules offering different capabilities that are briefly described in the following. In addition, plugins can be activated and deactivated on the fly, without interrupting the monitoring. Being a passive tool, live monitoring of Internet links, in which all flowing packets are observed, is the typical usage scenario. Fig. 1(a) sketches the common setup for a probe running Tstat: on the left there is the network to monitor, e.g., a campus network, that is connected to the Internet through an access link that carries all packets originated from and destined to terminals in the monitored network. The Tstat probe observes the packets and extracts the desired information. Note that this scenario is common to a wide set of passive monitoring tools. Therefore the problems faced when designing Tstat are common to other tools as well.

A. Monitored objects

The basic objects that passive monitoring tools considers are the *IP packets* that are transmitted on the monitored link. *Flows* are then typically defined by grouping, according to some rules, all packets identified by the same $flow_{ID}$ and that have been observed in a given time interval. A common choice is to consider $flow_{ID} = (ipProtoType, ipSrcAddr, srcPort, ipDstAddr, dstPort)$, so that TCP and UDP flows are considered. For example, in case of TCP, a new flow starts is commonly identified when the TCP three-way handshake is observed; similarly, its end is triggered when either the proper TCP connection tear-down is seen, or no packets have been observed for some time. Similarly, in case of UDP, a new flow is identified when the first packet is observed, and it is ended after an idle time.

As Internet conversations are generally bidirectional, the two opposite unidirectional flows (i.e., having symmetric source and destination addresses and ports) are then typically grouped and tracked as *connections*. This allows to gather separate statistics for *client-to-server* and *server-to-client* flow, e.g., the size of HTTP client requests and server replies.

Furthermore, the origin of information can be distinguished, so that it is possible to separate *local* hosts from *remote* hosts in the big Internet. As depicted in Fig. 1(a), traffic is then organized in four classes:

- *incoming* traffic: the source is remote and the destination is local;
- *outgoing* traffic: the source is local and the destination is remote;
- *local* traffic: both source and destination are local;
- *external* traffic: both source and destination are remote.

This classification allows to separately collect statistics about incoming and outgoing traffic; for example, one could be interested in knowing how much incoming traffic is due to YouTube, and how many users access Facebook from the monitored network. The local and external cases should not be considered but in some scenarios they can be present.

At packet, flow and application layers, a large set of statistics can be defined and possibly customized at the user's will. In case of Tstat, several statistics are already available, and they can be easily customized and improved being Tstat Open Source. A detailed description of all available measurement indexes can be found in [2].

B. Workflow analysis

As far as the analysis process is concerned, each observed packet is handed over to the analyzer plugins that are activated, as illustrated in Fig. 1(b). Following the Internet naming standard and going up in the protocol stack, layer-2 (L2) frame de-encapsulation is first done. Then, the network-layer (L3) header is processed. Given the datagram service offered by IP networks, at L3 only per-packet statistics, such as bitrate, packet length, are possible.

Going up to the transport-layer (L4) analysis, a set of common statistics for both TCP and UDP flows are maintained, e.g., packet and byte counters, round trip time (RTT) and throughput of the data download.

At the application-layer (L7), the main goal of a monitoring tool is to perform traffic *classification* task, that is to identify the application that generated the traffic. As traffic classification is known to be prone to fallacies, several approaches have been studied in the literature [6]. Each tools has then its peculiarities. In the case of Tstat, three different engines are available, each relying on different technologies. They are designed to work even when the complete packet payload is not available, that is a common situation in live networks monitoring, since, usually, only a limited portion of each packet is exposed to the sniffer due to privacy reasons.

The simplest engine is *Pure Deep Packet Inspection (PDPI)*. It uniquely identifies applications by matching a *signature* in the application payload. All the application signatures are collected in a dictionary, defining a set of classification rules, and are then checked against the current packet payload until either a match is found, or all the signatures have been tested. In the first case, the packet/flow is associated to the matching application, while in the second case it is labeled as "unknown". Signatures cover a large set of applications, ranging from standard email protocols to Peer-to-Peer applications, like Bittorrent, eMule, Gnutella, PPLive, and Sopcast. Extending and updating the signatures is a key issue with PDPI, as we will discuss later.

The second engine, named *Finite State Machine Deep Packet Inspection (FSMDPI)*, inspects more than one packet of a flow. Finite State Machines (FSM) are used to verify that message exchanges are conform to the protocol standard; to have a positive match, a specific sequence of matching rules have to be triggered. For example, if the first packet contains `GET http://` and the response carries `HTTP/1.0 OK`, the flow can be considered as HTTP. Using this approach, more complex signatures can be defined, allowing to identify more web based applications like YouTube, Vimeo, Facebook, Flickr, or chat services like MSN, XMPP/Jabber, Yahoo. Finally Voice over IP phone (VoIP) calls based on RTP/RTCP cannot be easily detected using PDPI and then FSMDPI classification is required.

To cope with applications that leverage on encryption mechanisms which make any DPI classifier useless, Tstat implements a *Behavioral classifier (BC)* engine that exploits statistical properties of traffic to distinguish among applications. For example, packet size or inter arrival time in flows carry information about the application generating the content, so that VoIP flows have very different characteristics with respect to data download flows. Using this approach, Tstat identifies encrypted traffic like the one generated by Skype and Obfuscated P2P-file-sharing of BitTorrent and eMule [3].

In Section III we present some results that exploit traffic classification capabilities of Tstat. While the performance and accuracy of the classifier are out of scope of this paper, overall, they have been found to “outperform [other] signature based tools used in the literature” when compared by independent researchers [7].

C. Input data

Software based monitoring tools like Tstat are designed to work in real-time when installed in operational networks. The software tool runs on a “probe”, i.e., a dedicated PC that “sniffs” traffic flowing on an operative link, as shown in Fig. 1(a). The libpcap library is the de-facto standard Application Programming Interface (API) to capture packets from standard Ethernet linecards under several Operating Systems. Dedicated hi-end capture devices such as Endace DAG or AITIA S1GED cards are also available on the market[1]. They offer hardware packet monitoring solutions that offload the main CPU while guaranteeing higher performance than software based solutions. Tstat supports both standard sniffing based on libpcap, and hardware solutions as the ones mentioned earlier.

Furthermore, Tstat can be also compiled as a “library” to allow an easy integration with already existing tools such as those typically deployed by an ISP which already has a monitoring solution. In the latter case, the ISP is free to customize Tstat and decide what packets should be further processed, so as to tune the amount of payload, filter packets, anonymized addresses for privacy purposes. In our experience, this approach has been very successful to facilitate the integration of Tstat with the monitoring tools of several ISPs around Europe and with other traffic analysis tools developed by the research community.

Besides live traffic analysis, monitoring tools are also commonly adopted to offline process packet level traces that have been previously collected. In this case, the tool can be used to inspect specific traffic for post-mortem analysis, or to develop more complex statistical analysis for advanced performance evaluation, or to double check the accuracy of any new index that is being developed. Since several trace file formats are available on the market, a variety of dump file formats should be supported, such as pcap, erf, etherpeek, snoop to name a few. Besides providing already a large set of trace file format input plugins, Tstat allows to easy integrate new formats thanks to its open and flexible design.

[1]http://www.endace.com, http://www.aitia.ai

D. Output statistics

Finally, each monitoring tool offers a set of output statistics that are strictly bound to the goal of the tool itself. For example, intrusion detection systems like Snort or Bro output the list of triggered alarms and violations, while traffic classification tools like Tie or Coralreef report statistics about application traffic shares. Considering Tstat, statistics are available with different granularities: per-packet, per-flow, and aggregated. At the finest level of granularity, *Packet traces* can be dumped into trace files for further offline processing. This output format is extremely valuable when coupled with Tstat classification capabilities: indeed, packets can be dumped per-application in different files. For example, it is possible to instruct Tstat to only dump packets generated by Skype and BitTorrent applications, while discarding all other packets.

At an intermediate level of granularity, *Flow-level logs* are text files providing detailed information for each monitored flow. A log file is arranged as a simple table where each column is associated to a specific information and each line reports the two unidirectional flows of a connection. Several flow-level logs are available, e.g., the log of all UDP flows, or the log of all VoIP calls. The log information is a summary of the connection properties. For example, the starting time of the VoIP call, its duration, the number of suffered packet losses, the jitter are all valuable metrics that allow to monitor the VoIP quality of service. Flow-level logs use much less space than the original packet level traces, and can be collected for much longer periods of time.

At an even higher level of granularity, Tstat gathers statistics about flows aggregates. Two formats are available in this case. *Histograms* are empirical frequency distributions of collected statistics over a set of flows. For example, the distribution of the VoIP call duration is automatically computed by considering all VoIP flows that were observed during each 5 minute time interval. To overcome the problem of storage space explosion of packet-traces, flow-level logs and histograms over time, the second available format is represented by *Round Robin Database* (RRD) [8], that allows to build a database that spans over several years by keeping the amount of space limited. RRD handles historical data with different granularities: newer samples are stored with higher frequencies, while older data are averaged in coarser time scales. This dramatically reduces the requirements in terms of disk space (a priori configurable) and, thanks to the tools provided by the RRD technology, it is possible to visually inspect the results. For example, RRD data collected by a Tstat probe can be queried in real time using a simple web interface [2], and plots of historical measurements over multiple sites can be shown. Results presented in this paper are obtained from the corresponding RRD data.

III. Traffic trends from different vantage points

After having presented the main Tstat features and characteristics, we now show Tstat capabilities through a few

TABLE I
PROBES CHARACTERISTICS

Location	Users	Technology	Type
Polish ISP	10k	ADSL	Home
Hungarian ISP	4k	ADSL	Home
Italian ISP	5k	ADSL	Home
Italian ISP	15k	FTTH	Home
Italian Campus	10k	LAN and WLAN	Campus

results and discuss some conclusions we drawn from our long experience in using it.

We have been collecting measurement data since 2005 in collaboration with several ISPs. A Linux-based Tstat probe has been installed and properly configured in different Points-of-Presence (PoPs).

A. Probe description

The main characteristics of the 5 probes are summarized in Tab. I, which reports the PoP location, the approximate number of aggregated users, the access technology and the type of customers distinguishing between Home or Campus users. As it can be observed, the set of probes is very heterogeneous: it includes Home users in three different countries, with ADSL or LAN and WLAN access technologies. Depending on the type of contract with the ISP and on the quality of the physical medium, ADSL technology offers the users different bitrates, ranging from 2 to 20 Mb/s downstream and up to 1024 kb/s upstream. Fiber to the Home (FTTH) customers are offered 10Mb/s full duplex Ethernet connectivity, while Campus users are connected to a 10Gb/s based Campus network using either 100 Mb/s Ethernet, or IEEE 802.11a/b/g WiFi access points. The Campus network is connected to the Internet via a single 1 Gb/s link and a firewall is present to enforce strict policies, to block P2P traffic (unless obfuscated), and to grant access to only official servers inside the campus.

Probes were upgraded several times to update the Tstat version and to include advanced features, so as to enhance traffic classification accuracy and augment the number of protocol signatures. All probes are configured to continuously collect RRD information.

B. Traffic share and trends

We first present results covering the May 1st, 2009 to Oct 31th, 2010 period. Figure 2 shows the traffic breakdown for incoming traffic, i.e., traffic received by customers. The applications generating the largest amount of traffic are highlighted using different colors. Over time, we enhanced the classification portfolio of Tstat by adding both PDPI/FSMDPI rules and statistical signatures. For example, since June 2009 we have been collecting statistics about both Streaming Applications, such as YouTube, Vimeo, Google video and other flash-based streaming services, and File Hosting Web based services like RapidShare or MegaUpload that allow users to share large files. Light and dark pink colors highlight them in the plots. Developed and double checked in the Campus network first, we then deployed these capabilities into other probes. Similarly, since December 2009 the BitTorrent obfuscated traffic (plotted in light green) is correctly identified by Tstat, and the more recent BitTorrent UDP based data transport protocol named uTP [9] is correctly classified since July 2010 (dark red). This latter classifier was developed while investigating the cause of the sudden increase of UDP traffic share that is clearly visible in the Hungarian vantage points during February 2010. This is an example of the usage of Tstat to effectively support traffic monitoring.

Several considerations can be derived from the presented results.

- Before the BitTorrent adoption of uTP protocol, the volume of UDP traffic was marginal in all vantage points but in the Italian ISP. This is due to this ISP offering Video on Demand (VoD) services over UDP that makes the volume of VoD UDP traffic in this network about 10% of the total. Customers of the same operator are offered native VoIP service using standard RTP/RTCP protocols over UDP. Still, the volume of traffic due to VoIP is almost negligible, accounting for less than 2% of total traffic (in purple color in the figure). Nowadays, UDP traffic can top 20% of total volume, depending on the popularity of BitTorrent-uTP or VoD applications. Therefore, the widely popular statement that UDP traffic is negligible does not hold anymore.
- Applications usage is very different at different places. For example, in Poland the fraction of HTTP traffic is predominant, with more than 60% of traffic due to several applications adopting HTTP protocol. In both the Italian ISP PoPs, instead, Peer-to-Peer (P2P) applications amount to more than 50% of traffic, with eMule clearly being preferred over BitTorrent. In Hungary, on the contrary, BitTorrent is more popular (with a traffic share above 20%), while an almost negligible amount of traffic that is due to eMule. Finally, note that in the Italian Campus network the fraction of P2P traffic is marginal being the firewall very effective in blocking such traffic.
- Some slow long-term trends are clearly visible. For example, P2P traffic share is generally decreasing, while streaming applications are becoming more and more popular with a share that has reached more than 20% in Poland, and is above 15% in other PoPs. Interestingly, there is a corresponding positive trend for File Hosting applications, which are eroding important percentage of traffic to P2P file sharing applications. Indeed, the same content can be retrieved by users through P2P or File Hosting technologies. The latter is nowadays becoming more and more popular among users since it offers much better performance.
- While the above mentioned changes in traffic shares are typically slow, sudden changes are possible due to changes in the application. For example, as already mentioned, the popular μtorrent application was updated during February 2010 to use by default the uTP transport protocol instead of TCP. Correspondingly, there is an increase of UDP traffic clearly visible in some probes. Similarly, RapidShare changed the application protocol during September 2010, and this change fooled the PDPI classifier. An artificial drop in File Hosting traffic is then observed in those vantage points in which RapidShare is popular, e.g., in Poland.
- Traffic shares are very stable and little variations are visible among different days. Only in the Campus network,

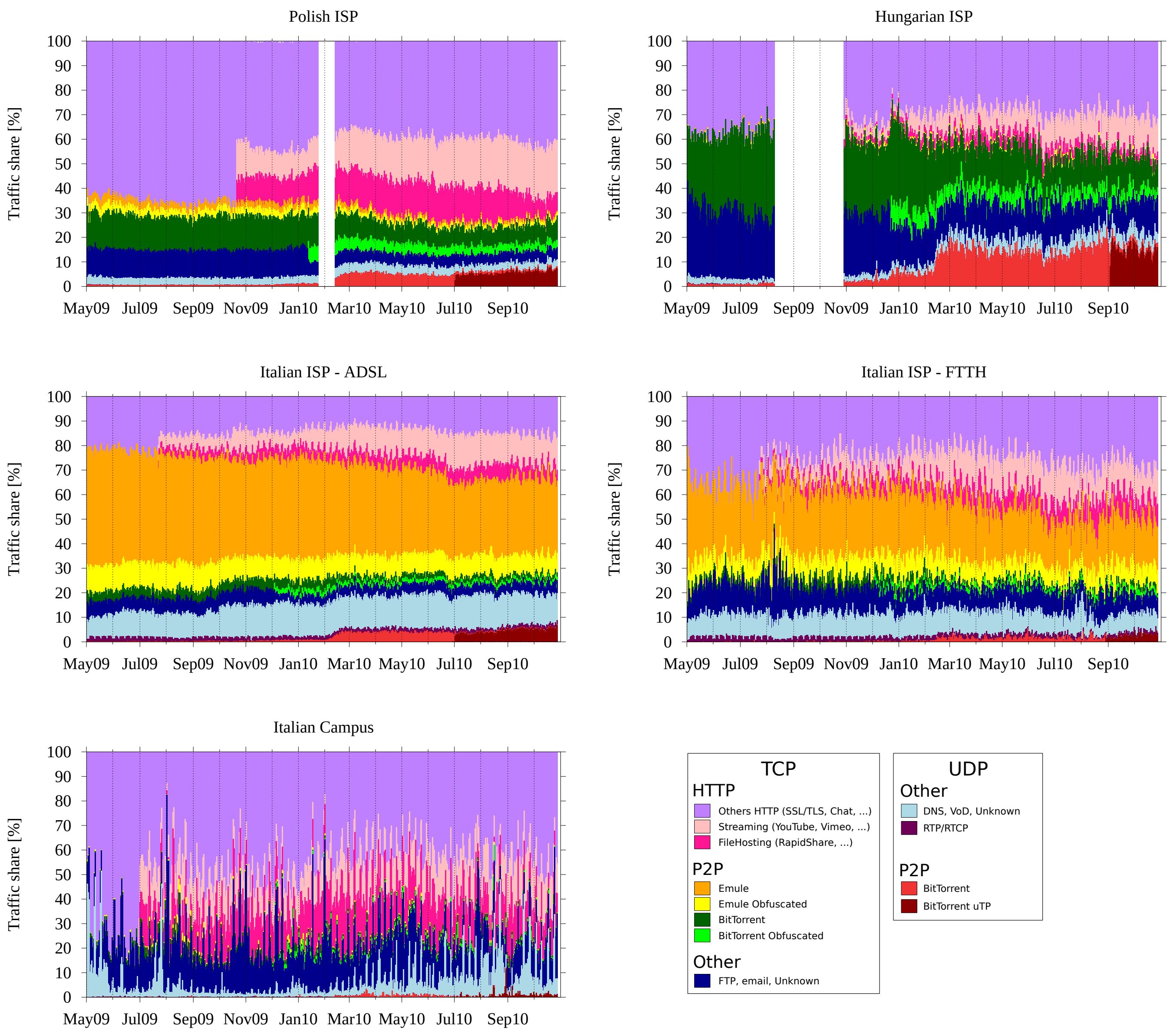


Fig. 2. Comparison of traffic as observed on 5 different traffic probes.

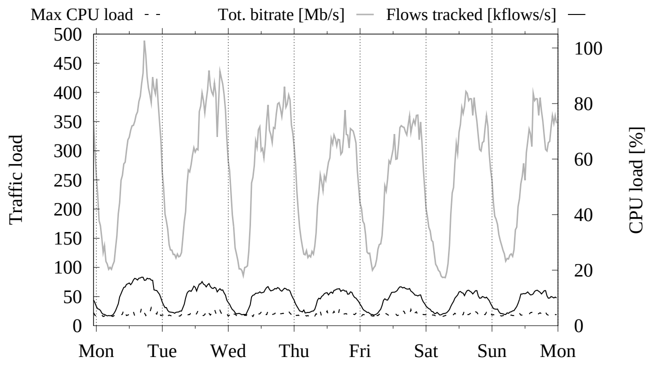
the variability is very high and the weekly pattern is clearly visible (see also the figure and related comments in the next section). Indeed, during the weekend, few users are present in the campus and little traffic flows on the link. This causes the application usage pattern to be different.

While it is out of scope of this paper to provide a detailed analysis of Internet traffic trends and user habits, the presented results highlight the importance of constantly monitoring the network with a flexible tool that has to be constantly upgraded and enhanced to follow its changes.

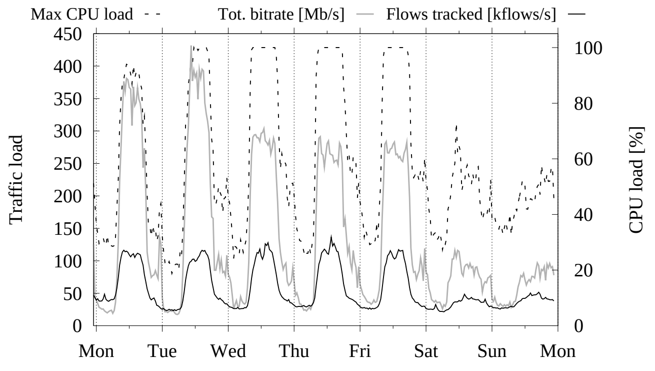
IV. Scalability issue of software based monitoring tools

When implementing a live monitoring tool, the knowledge of the maximum sustainable load that the probe can handle is one the most critical issues that must be faced. Indeed, as seen in the previous section, Internet traffic widely changes over both time and space. In a finer timescale, traffic is known to exhibit even larger variability considering both the packet and flow levels. For example, packet level burstiness can stress the sniffing hardware so that packet bursts can arrive at very high speed. Packet capturing, filtering and timestamping are then critical, especially if implemented in software. Similarly, bursts of new flows can stress the per-flow operations, so that memory management becomes typically a bottleneck.

While Tstat is as an example of advanced traffic monitoring tool, most of the operations it handles are common to any flow level sniffer and monitoring tool. Indeed, similar data structures must be used to store basic per-flow information such as flow identifier, packets and bytes counters, timestamp and the classification status. Notice that flow structures must be accessed and updated for each packet: hence, efficient data structures like hash-tables must be considered, where



(a) Italian ISP FTTH probe.



(b) Italian Campus probe.

Fig. 3. Total link bitrate, number of flows and maximum CPU utilization during a typical week.

collisions are minimized and eventually handled using chaining. Further optimizations of memory management are also needed; freed structures should be manually handled as reuse lists by a garbage collector, so as to avoid generic and expensive garbage collection routines to kick-in and slow down the main analysis operations.

In [10] we extensively analyzed the computational complexity of the Tstat analysis workflow, showing that even with off-the-shelf hardware it is possible to run advanced analysis techniques on several Gb/s worth of traffic in real-time.

To provide some examples of the typical workload that Tstat has to support, and to highlight some critical points in the design of a flow-sniffer, Fig.3 shows the evolution a one week long period of time of the total link bitrate (gray line), number of tracked flows (black line) and maximum CPU utilization (dotted line), i.e., the total time spent by the CPU in running Tstat, including both kernel and user space CPU time. Measurements refer to a time window of 5 minutes. The results for the Italian ISP FTTH and Italian Campus probes are reported on the top and bottom plots, respectively; results from other probes are not reported for the sake of brevity.

Considering the total link bitrate, the two probes handle approximately the same amount of traffic, which tops to nearly 500Mb/s at the peaks. Notice that the peak-hour occurs at different times, reflecting the different user habits of Home and Campus users. The number of active flows is also very different, with the Campus probe having to handle a per-flow load which is about two times higher. This is due to the different traffic mix generated by Campus users, as previously shown in Fig. 2. Therefore, hash table sizes must be correctly tuned to support the various values of the load.

In the CPU load curves, we see a very different behavior: the Italian ISP probe exhibits a very low maximum CPU utilization, which is not correlated with either the packet or flow level patterns. On the contrary, the Campus maximum CPU utilization is always above 30%, and it tops 100% during sustained traffic load. Investigating further, we pinpointed this to be due to the packet capturing input module, which is based on a common Gigabit Ethernet linecard in the Campus probe, while the Italian ISP probe relies on dedicated Endace linecard. Based on our experience indeed, the major bottleneck is due to the linecard-to-memory communications, which can overload CPU by generating a large number of Interrupt Requests (IRQ) per second, i.e., one for each received packet. Dedicated traffic capturing devices solve this problem by implementing timestamping functionalities and Direct Memory Access (DMA) based transfers of packet batches. The CPU utilization figures of the other probes, not shown in the paper due to lack of space, confirm this. All ISP probes are indeed equipped by dedicated hardware capturing linecards so that the maximum CPU utilization remains very limited even if they have to handle a large volume of traffic, topping to about 1.5Gb/s.

In summary, with common hardware it is possible to monitor several Gb/s volumes of traffic in real time, provided the packet capturing is performed with efficient hardware that offload the CPU from the per-packet memory copy and timestamping operations. Similarly, efficient memory management algorithms must be adopted to perform per flow operations, which optimize both the flow lookup performed for every packet, and garbage collection mechanisms required to avoid memory starvation.

V. Conclusions

In this paper, we described our experience in using Tstat, a software based Internet traffic monitoring tool that we have being developing for the past 10 years. Presenting measurements collected from several ISP networks, we have shown that Internet traffic widely changes over both time and space: application shares are different at different networks even if common trends are visible due to slow changes in applications popularity; however, sudden changes are observed after the deployment of disruptive technologies made by applications themselves. We then discussed the implication of using software based solutions for traffic monitoring showing that moderate volumes of traffic can be monitored with common hardware, provided that efficient packet capturing devices are used, and proper memory management is implemented.

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