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ANALYSING TRAFFIC CACHEABILITY IN THE ACCESS NETWORK AT LINE RATE

ANALISER LA CACHEABILITÉ DU TRAFIC DANS LE RESEAU D'ACCES AU DÉBIT DE LIGNE

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THÈSE

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Abstract

There is a lot of web traffic in the networks of Internet Service Providers (ISP), and caching surely looks like a promising way to both reduce the load on the ISP networks and to improve the user experience. In particular we want to assess if there are any gains in caching at the edges of the network, where many small and cheap caches can be easily placed, ideally by using an Information Centric Networking (ICN) approach, since it allows for pervasive caching out of the box.

We had the unique opportunity to place our own probe in the live network of Orange in Paris, in two different locations in the access network. There, using a high-performance capture and Deep Packet Inspection (DPI) analysis tool developed from scratch during this thesis, we captured and analysed the Web traffic of several thousands of Orange clients on 2 full duplex 10Gbps optical links.

Using the commonly used metrics of Cacheability and Traffic Reduction we measured the amount of requests and traffic that could be cached by a cache placed in the access network. First we found the best timescale for the cache, which turned out to be around one day in our case, and we found that around 40% of the requests and 30% of the traffic can potentially be saved. We then estimated the size needed for a cache placed in the access network, on the home router of the client, or in both locations. In our cases we found a lower bound of 100GB for the cache in the access network and 100MB in the home router.

The estimate of the cache size was then used to perform some simulations with an actual cache simulator, in order to validate the metrics, and we found that the estimates obtained with the simple metrics match with the performance of an LRU cache. In order to study the impact of the temporal locality of the requests, we also ran the simulation after shuffling the request stream at different timescales, and we found out that shuffling has indeed a negative impact on the performance of the caches, even when performed on small timescales.

Since the amount of output generated by the tool is very big (hundreds of gigabytes

per day), a scalable analysis solution was needed. We therefore decided to use Hadoop to process the output of the tool to generate the statistics. We tried using the PIG language, but the performances were not satisfactory, so we used the Hadoop infrastructure directly in Java. We measured the impact of some performance optimizations, and found that some advantages could be indeed achieved, although small.

With a scalable analysis system in place, we could then concentrate on the performance and accuracy of different strategies used to identify the requested objects. We found that using the size of the objects as additional identifier increases the accuracy, but only a proper stateful reconstruction of all the partial requests yields the most accurate results.

We observe that caching is possible even in the fast-path of the network, thanks to the relatively small sizes needed for the caches. By means of measurement and statistical analysis, this thesis shows that caching in the access network is a real opportunity for ISPs.

The main contributions of this thesis are the following:

— Traffic analysis tool: design and development of a real-time analysis tool for high performance line speed dissection and analysis. Notably the tool can analyse HTTP transactions at 10Gbps with a single core.

— Timescale analysis: inferring the timescale at which it makes sense to cache in the access network (Sec. 4.2.1). We find out that one day is the optimal timescale for cacheability analysis at the access network.

— Content popularity analysis: analysing and characterizing content popularity over a meaningful timescale (Sec. 4.2.2).

— Sizing of caches: determining a good value for a real-world cache in the access network, and validate it through simulations (Sec. 4.3)

— Object identification strategies: analysing the impact of different object identification strategies on the cacheability statistics. (Sec. 4.4)

— Map-Reduce framework: design and implementation of a scalable analysis system using the Hadoop Map-Reduce framework.

— Map-Reduce benchmarking: measure the impact on the performance of Hadoop of different optimizations.

Keywords: Caching – Content Delivery Networks – Information Centric Networking – Traffic Analysis – Cacheability – Big Data

Résumé

Dans les réseaux des ISPs (Internet Service Providers – fournisseurs d'accès à internet) il y a beaucoup de trafic web, et cacher semble sûrement un moyen prometteur pour reduire le charge sur les reseaux des fournisseurs et pour ammeliorer l'experience utilisateur. En particulier nous souhaitons évaluer si il y a des advantages en cacher dans le bord extern du reseau, où est possible de placer beaucoup de caches petites et pas cheres, idéalement en utilisant un approche ICN (Information Centric Networking – Reseau Centré sur l'Information), parce que il prévoit naturellement le caching partout.

Nous avons eu la possibilité de placer notre sonde dans deux locations differentes dans le reseau d'accès de Orange à Paris. Là, en utilisant un outil d'analyse à hautes prestations qui effectue DPI (Deep Packet Inspection – Inspection Aprofondie des Paquets), dévéloppé entièrement pendand cette thèse, nous avons colleté et analysé le trafic Web de diverses milliers de clients Orange sur deux liens optiques à 10Gbps full-duplex.

Nous avons mesuré la quantité de requêtes et de trafic qui peut être caché par une cache placé dans le reseau d'accès en utilisant les métriques de Cacheabilité (Cacheability) et Reduction de Trafic (Traffic Reduction). Du premier façon nous avons determiné l'echelle temporelle meilleur, dans notre cas un jour, et nous avons trouvé que environ 40% des requêtes et 30% du trafic peut potentiellement être épargné. Nous avons alors estimé la taille necessaire pour une cache placé dans le reseau d'acces, dans le routeur domestique, ou les deux. Dans notre cas, nous avons trouvé une limite inférieur de 100Go pour la cache dans le reseau d'acces, et de 100Mo dans le routeur domestique.

La taille estimée de la cache a été en suite utilisé pour effectuer des simulations avec un simulateur réel, afin de valider les metriques, et nous avons trouvé que les estimations obtenues avec les metriques simples correspondent avec les prestations de une cache LRU réel. Pour étudier l'impacte de la localité temporelle des requêtes, nous avons aussi effectué une simulation avec le flux de requêtes mélangé au hasard, et nous avons trouvé que mélanger a effectivement un impact négatif sur les prestations des caches, même à échelles temporelles petites.

La quantité de données générées est beaucoup grand (centaines de gigaoctets par jour), donc une solution d'analyse scalable était necessaire. Nous avons donc decidé d'utiliser Hadoop pour processer les données générées par l'outil d'analyse. Nous avons essayé d'utiliser le langage PIG, mais les prestations n'étaient pas satisfaisant, et donc nous avons utilisé l'infrastructure Hadoop directement ne Java. Nous avons mesuré l'impacte de certaines optimisations des prestations, et nous avons trouvé que certaines avantages peuvent effectivement être attaintes, bien que petits.

Avec un system d'analyse en place, il était possible de mesurer les prestations et la précision de differents strategies utilisé pour identifier les objets demandés. Nous avons trouvé que utiliser la taille des objets comme identificateur additional augmente la precision, mais seulement une analyse correcte de toutes requêtes partielles produit les resultats les plus exactes.

Nous observons que cacher est possible même dans le chemin chaud du reseau, grâce aux tailles relativement petites des caches. Nous arrivons à cette conclusion en analysant le trafic réel de plusieurs milliers de clients Orange à Paris, avec un outil d'analyse développé pour ce but. À travers de mesures et analyses statistiques, cette thèse montre que cacher dans le reseau d'accès est une vraie opportunité pour les ISPs.

Les contributions principales de cette thèse sont les suivantes :

— Outil d'analyse du trafic : conception et développement d'un outil d'analyse en temps réél pour dissection et analyse à hautes prestations et à vitesse de ligne. Notamment l'outil peut analyser du trafic HTTP à 10Gbps avec un seul cœur.
— Analyse de l'échelle temporelle : inférer l'échelle temporelle dans laquelle il y a des avantages concrets pour cacher dans le reseau d'accès.
— Analyse de la popularité des contenus : analyser et charactériser la popularité des contenus das une échelle temporelle significative.
— Dimensionement des caches : determiner une bonne taille pour une vraie cache dans le reseau d'accès, et la valider avec des simulations.
— Stratégies d'identification des objets : analyser l'impact de différents strategies d'identification des objets à cacher sur les statistiques de cacheabilité.
— Système Map-Reduce : conception et implementation d'un système d'analyse évolutif en utilisant Hadoop, un système Map-Reduce.
— Analyse comparative du système Map-Reduce : mesurer l'impact sur les prestations de Hadoop de différentes optimisations.

Mots-clés : Cacher – Reseaux de Livraison des Contenues – Reseau Centré sur l'Information – Analyse du Trafic – Cacheabilité – Mégadonnées

Contents

Chapter 1

Introduction and motivation

Internet traffic is nowadays skyrocketing, and more and more services are being served through the web using HTTP[1]. A growing number of people are using more and more connected devices, which, due to technologic progress, have an increasing amount of bandwidth at their disposal. The amount of 2G mobile connections is decreasing in favour of faster 3G and 4G, and in a few years ultra fast 5G mobile internet will be available for consumers.

This huge increase in available bandwidth spurred the creation and/or growth of bandwidth intensive applications, like Video on Demand (VoD) and Subscription Video on Demand (SVoD), such as Netflix or Youtube. Naturally many other applications also appeared, like file sharing or Voice over IP (VoIP), but they only constitute a marginal share of the total traffic, either because of the nature of the application, or because of throttling. Moreover they are not normally served over HTTP, so they are not relevant to this thesis.

Video streaming thus constitutes a huge part of internet traffic, and while in the past such services relied on proprietary transport protocols (like RTP and RTSP), streaming is nowadays performed almost exclusively over HTTP. By 2019, Cisco estimates that 80% of internet traffic will be due to video streaming[2].

The spread of Web-based content delivery solutions has multiple root causes (e.g. enhanced flexibility and ease of access from a vast set of user terminals, mostly mobile) and consequences. In particular, today Subscription Video on Demand (SVoD) consumers expect high Quality of Experience (QoE) when accessing their videos from any device inside and outside their home (TV, HDTV, smart-phones, tablets, media players).

1.1 Content Delivery Networks (CDNs)

At the end of the 20th century, Internet backbones were not as fast as they are today and clients had significantly slower connections (dialup was still common). Websites, especially those geographically far from clients were slow and had huge latencies. Content Delivery Networks (CDNs) were born to address this issue. The idea is straightforward: disseminate caches around the world in order to assure that a cache is always close enough to the clients; the clients are directed to a nearby cache depending on their location. CDN operators get revenue from the owners of the sites that use their network. This idea, initially developed only to increase the performance of end-customer-facing websites, also has the benefit of reducing traffic in the backbones.

Nowadays, fast intercontinental links allow for almost instantaneous access to any website anywhere in the world, thus diminishing the impact of their original task. But in the meantime CDNs have evolved to provide additional services, thus increasing their relevance once again.

First of all, CDNs provide high availability and high performance even in case of massive amounts of traffic, since the origin servers (the ones hosting the original content) will only see a very tiny fraction of the requests. This allows for small (and therefore cheap) servers handled directly by the publishers. Having many caches distributed globally also helps against Distrubuted Denial of Service (DDoS) attacks, since multiple clients spread out geographically trying to hit the same server will in fact hit different caches.

The biggest CDNs operators are now putting their caches directly inside the networks of Internet Service Providers (ISPs), in order to further minimize the latency, at the cost of paying the ISPs for hosting the caches in their networks.

The caching advantages of CDNs also imply that websites will generate less traffic on the backbone, yielding savings for the website operators, since they have to pay for less traffic on the backbone; for the ISPs, since their backbone links now do not need as many upgrades; and finally for the CDN operators, because they get paid for their services.

Still, even when placed directly in the network of ISPs, CDN caches are usually very large and serve hundreds of thousands, or even millions of clients.

Since CDNs allow ISPs to save traffic, the ISPs themselves started to deploy their own CDNs to cash on the advantages; ISP-run CDNs are typically used for VoD, SVoD and TV broadcast. Traditional IP multicast fails to satisfy the large set of requirements needed: multicast is not reliable because it's UDP only, it does not have any form of congestion control, and finally and very importantly, multicast is also often misconfigured,

and one single misconfigured node along the path is enough to render it useless. This forces ISPs to build their own video services on top of CDN systems, and by running the CDNs themselves, the ISPs can better optimize the content for their clients and networks.

Section 2.1 contains references to related works about CDNs.

1.2 Information Centric Networking (ICN)

Since web traffic is the overwhelmingly biggest share of the total internet traffic, the classical point-to-point paradigm of the net turns out to be sub-optimal. A better approach, taking inspiration from the ideas that drive CDNs, is Information Centric Networking (ICN).

The fundamental idea of ICN is that the content is the basic unit; packets on the wires are either content or requests for specific content. There are no connections between a client and a server, just requests sent to the network, and replies with the requested objects. Each ICN router has a small cache (usually called Content Store); this allows to cache popular objects in the network locations where they are most needed. This also allows for interesting mesh-like and/or delay tolerant networks.

Having a global network of caches is almost like having a huge global CDN that serves all websites; popular content will be close to the end-users with high probability, origin servers are spared most of the load (thus handling high traffic or DDoS automatically out-of-the-box). The differences with actual CDNs are

— less control: ICN does not give control to the originator of the content about where the content will be cached

— size: most caches will be small, especially near the edges of the network; this might not be efficient

— no more CDNs: if every object is automatically cached in the network by the network itself, there is no more need for CDNs, at least in the form we know them currently.

This is indeed a huge paradigm shift, like the one from circuit networks to packet switching, and requires huge changes in the software and in the internet infrastructure. The advantages and disadvantages of this paradigm need to be studied thoroughly, since only very good results can possibly lead to its adoption. In particular the effectiveness of caches with a small user fanout needs to be assessed.

Section 2.1 contains references to related works about ICN.

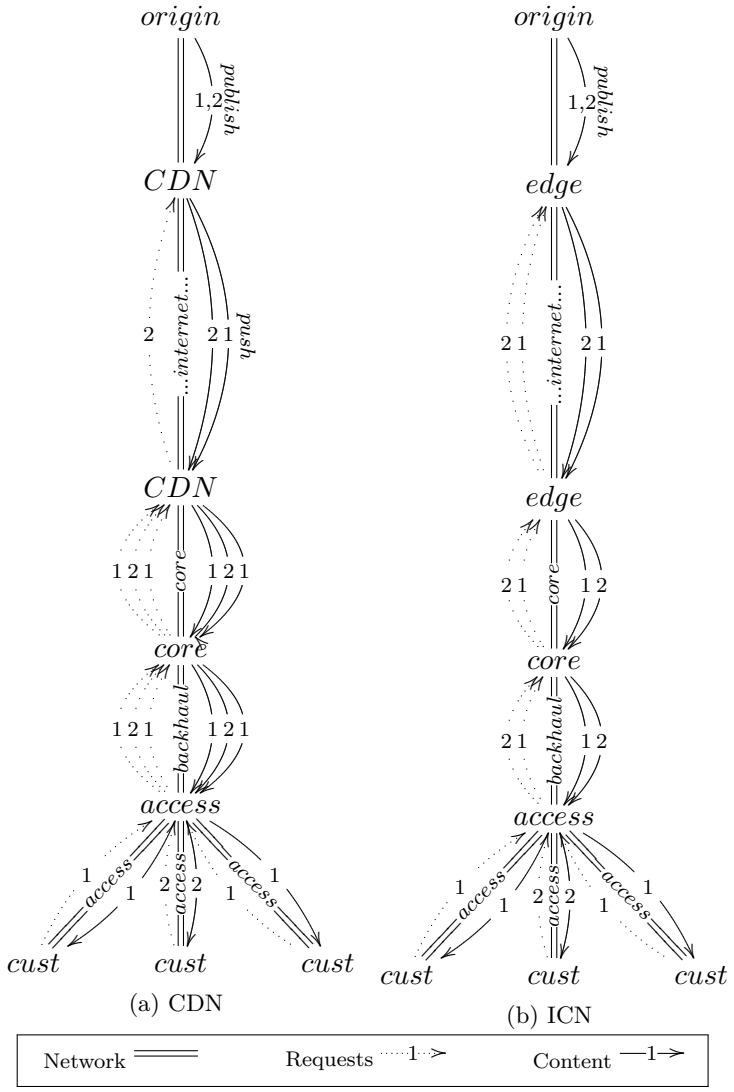


Figure 1.1: Object delivery model: CDN vs ICN. Example of the delivery of a very popular object (1) and a less popular one (2).

1.3 ISP dilemma

Today's model presents various business weaknesses since it relies on third-parties (e.g. Netflix) to provide web services, whose quality depends on someone else's network infrastructure (one or multiple ISPs). For video-centric services, the relation between investments and revenues tends to be unbalanced when third-party content providers do not recognize any additional revenue to the ISPs which, instead, shoulder investment

and operational costs to deliver additional traffic shares at no incremental revenue. The end customer is not eager to pay more to solve the dispute among the two parties if this requires to lose Internet access flat rate. The dispute involving Netflix and Comcast, Verizon and AT&T in the USA is one good example displaying the difficulties and frictions in this market [3].

ISPs are then faced with a dilemma: increase the capacity towards the content providers, shouldering the costs, or providing a sub-par service to their customers, causing complaints and potentially lawsuits.

1.4 Micro CDNs

To solve the issues between ISPs and content providers, we propose a novel approach for ISP content delivery, referred to as *micro CDN*[4], combining the service flexibility of typical Web based CDNs with efficient redundant traffic reduction as in an IP multicast tree. A micro CDN makes use of small storage that can work at high speed and can take advantage of fast memories. A few technologies suitable to achieve this goal already exist, i.e. JetStream [5], AltoBridge [6] and also Open Connect [7]. However, they provide no standardized architecture, they do not interoperate and they do not support every kind of Web content. We believe that an ICN approach can satisfy the aforementioned goals, in particular we consider the content-centric networking (CCN) architecture (a.k.a. NDN)[8]; by embedding a service-agnostic content caching into the network architecture, CCN may provide a common underlying network substrate for the deployment of next generation CDN systems.

While micro CDNs are technologically feasible, ISPs would have incentives in deploying them only provided that gains are sizable. By means of measurement and statistical analysis, this thesis shows that caching in the access network is a real opportunity for ISPs.

1.5 Performing Cacheability Analysis

Deciding the location and size of the caches in a network is fundamental for maximizing the efficiency and the gains. On the other hand, such decisions can only be performed with enough information about the requests that are issued on the network segment that is to be serviced by the cache. Gathering such information is definitely not trivial due to the huge quantities of data involved in the process to perform this very estimation. Compromise solutions are detrimental: for instance, *sampling* the requests

process may lead to optimistically filter out a bulk of unpopular content, overestimating caching gains; *capping* the maximum data rate limits the analysis to the edge of the network where the lack of statistically significant multiplexing can adversely impact the estimation, leading to caching gains underestimation; operating on *flow records,* implies losing important details (e.g., range requests, cookies, etc.) for object identification, which could again lead to overestimation. Clearly, combining any of the above simplification can either lead to uncontrolled error amplification or compensation, which a scientifically sound study should take care of avoiding.

Fortunately, the last decades have seen a flourishing ecosystem of software tools [9, 10, 11, 12, 13, 14] that allow to naturally cope with huge data quantities and that are labeled with the name of "big data" solutions. The best known example is represented by the Map-Reduce paradigm, initially proposed by Google[15], of which the most popular implementation is Yahoo's Hadoop[10]. Initially proposed for distributed log processing, the paradigm has been quickly applied to other areas, including network and traffic analysis [16, 17, 18, 19, 20, 21, 22]. The reasons of this success are clear considering that, provided that the problem at hand is amenable to parallel computation, the Map-Reduce paradigm offers horizontal scalability. In other words, once a distributed analytic has been developed, it can be applied to larger datasets by parallelizing computation over enough hardware resources (i.e. CPU and memory). In the age of digital data deluge, and in reason of the expected increase of traffic rate, this property practically becomes a requirement to maintain computational feasibility (i.e., gathering results, in a furthermore useful time).

It follows that the problem of traffic cacheability estimation is worth attacking with a big data approach, which is precisely the aim of this work. Our previous work in this area has tackled the analysis of traffic cacheability with more traditional techniques. Yet we faced significant scalability challenges to apply the same methodology on larger dataset – where larger is intended here in temporal, spatial and line-rate respects. In this thesis we solve these scalability issues with Map-Reduce.

1.6 Contributions

We observe that caching is possible even in the fast-path of the network, thanks to the relatively small sizes needed for the caches. We reach this conclusion by analysing the live traffic of several thousands of Orange customers in Paris, using an analysis tool developed for the purpose.

The main contributions of this thesis are the following:

— Traffic analysis tool: design and development of a real-time analysis tool for high performance line speed dissection and analysis. Notably the tool can analyse HTTP transactions at 10Gbps with a single core.
— Timescale analysis: inferring the timescale at which it makes sense to cache in the access network (Sec. 4.2.1). We find out that one day is the optimal timescale for cacheability analysis at the access network.
— Content popularity analysis: analysing and characterizing content popularity over a meaningful timescale (Sec. 4.2.2).
— Sizing of caches: determining a good value for a real-world cache in the access network, and validate it through simulations (Sec. 4.3)
— Object identification strategies: analysing the impact of different object identification strategies on the cacheability statistics. (Sec. 4.4)
— Map-Reduce framework: design and implementation of a scalable analysis system using the Hadoop Map-Reduce framework.
— Map-Reduce benchmarking: measure the impact on the performance of Hadoop of different optimizations.

1.7 Organization

This thesis is organized as follows. In Chapter 2 we present other works related to the topics of this thesis: about ICN and CDNs, about other internet traffic capture and analysis tools, about other cacheability analysis and about MapReduce frameworks. Chapter 3 introduces the capture tool developed during this PhD, the network topologies where it was deployed and the hardware it runs on, and the dataset it collected. Chapter 4 presents the cacheability analysis of real traffic, including timescale analysis and simulations of different scenarios. Chapter 5 focuses on the big-data approach needed to process the sheer amount of data collected, including parallelization of cacheability analysis and optimization for speed. Finally in Chapter 6 a perspective of the achieved results and future topics is given.

Figure 1.2 shows a workflow scheme of the capture and analysis process, referencing the chapters where the different parts are discussed. Notice that the presentation infrastructure was developed by Wuyang Li, and not by the author, its description is included in Appendix C for reference purposes.

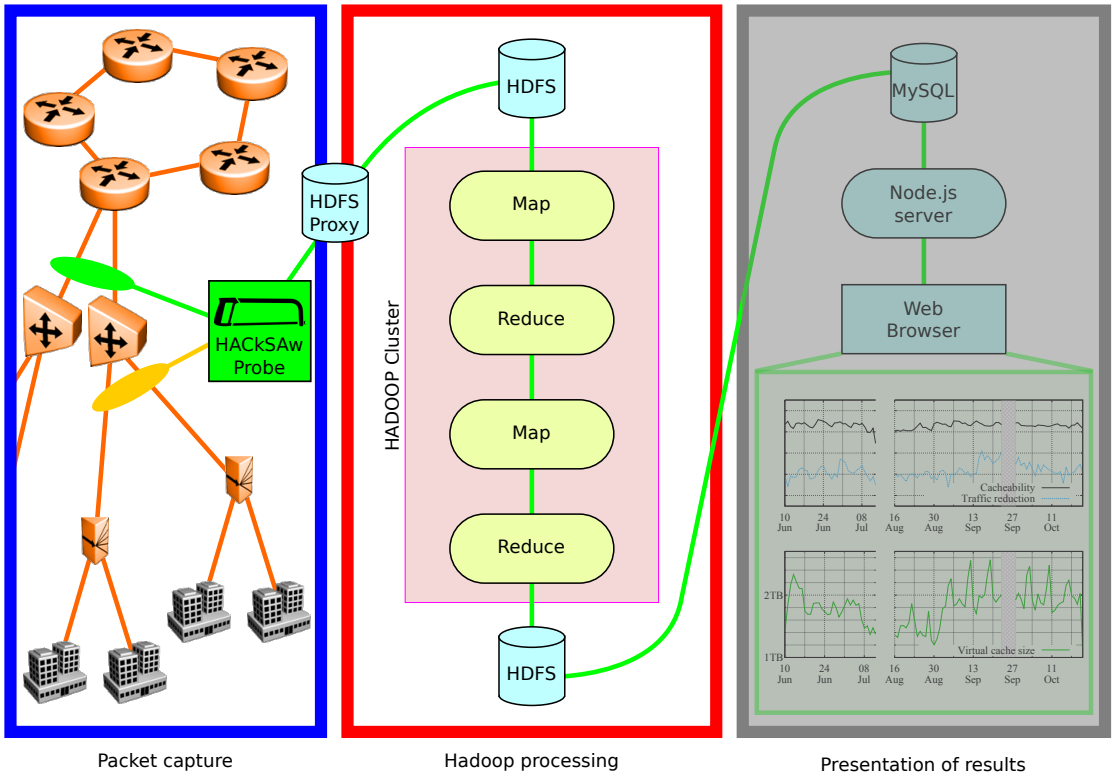


Figure 1.2: Workflow overview of the capture and analysis process. Chapters 3 and 4 introduce and describe the part on the left, Chapter 5 describes the middle part, while the presentation of the results is described in Appendix C.

Chapter 2

Related works

This chapter gives an overview on works related to the topics touched in this thesis. We start from ICN and CDNs, since there are many studies and articles about architectural simulations and cache placement, dimensioning, and decision. We will provide an overview on the existing traffic capture tools, explaining why we needed to write a new tool. We will also present a quick comparison of the types and sizes of datasets collected in other works. Subsequently we will introduce some works that also perform cacheability analysis, although with different methodologies than us. Finally we willprovide an overview of differnt existing Big Data and MapReduce frameworks.

2.1 ICN/CDN

In the last few years, a significant body of work has tried to measure the relation between the amount of resources and efforts to achieve the gains promised by CCN[23, 24]. Most of these works are based on network simulations in some very specific scenarios, none of them taking into account the ISP infrastructure. They focused instead on content placement and caching performance no deeper than the PoP (Point of Presence). Other works[25, 26], have shown significant gain of CCN in some relatively downsized network settings. The drawbacks of computer simulation and network experimentation are that, while being valuable, they do not allow to generalize the results for realistic workloads, which are difficult to accurately model and even synthesize. Analytical models of such systems [27, 28] allow to quickly evaluate the relation between QoS, network capacity and users' demand, but they either fail to provide reliable performance predictions or must be tuned, a posteriori, using a data sample [29],[30]. Additionally, precise values of Web content *size* are often neglected in previous works, which are based

on the analysis on HTTP requests only, neglecting all HTTP replies and resulting in possibly biased evaluations; the most notable exceptions are [31] and [32], which use a measurement methodology similar to ours and analyze either HTTP request and replies in radio mobile networks. See chapter 3 for more details about the capture tool and the gathered datasets.

The problem of cache placement (i.e. where to cache), dimensioning (i.e. how much to cache) and decision (i.e. what to cache) have thus received much attention in recent literature. In [24] it is shown, by using trace driven simulations, that a simpler caching architectures also deliver sizable advantages. [33] provides an analytical characterization of bandwith and storage caching under some generalistic assumptions regarding content demand, network topology, and content popularity. [34] gives a closed form formula to estimate the throughput in function of parameters like hit ratio, content popularity, content and cache size, which is then validated with a chunk-level simulation. [35] provides a mathematical explanation of the Che approximation, showing that it holds for ICN. In [36] existing LRU approximation algorithms are used as basis for a new algorithm that can be used to approximate LRU cache networks; per-cache and per-network performance measurements and error analysis are also performed. [37] uses a YouTube-like catalog to perform a performance evaluation of CCN, finding that a simpler caching architecture is good enough, and that the catalog and the content popularity are fundamental parameters. By performing a packet-level simulation, [38] investigates the tradeoffs in ICN between forwarding requests to known copies of the object and towards unknown paths. Similarly, [39] investigates a dynamic request forwarding approach for ICN, similar to Q-routing. [40] denostrates the advantages of stateful routing, in particular with respect to name prefix hijacking, failed link avoidance, and multipath routing. In [41] ICN simulations are performed with a YouTube-like catalog and large caches at the nodes to asses the usefulness of topological information when allocating cache sizes. In [42] a probabilistic caching strategy for ICN is developed and compared to other caching strategies. In [43] a content caching scheme is proposed that allocates space in the caches in function of the popularity of the objects. On the other [44] hand shows that random caching in a single node on the delivery path provides similar or even better results than pervasive caching, both on synthetic and real topologies. In [4] we show the advantages of caching at the edge of the network, like ICN would do natively, and we show that there are clear advantages. [45] shows instead that pervasive caching yields clear advantages when caching decisions and forwarding are tightly coupled, in particular when iNNR (ideal Nearesr Replica Routing) and LCD (Leave a Copy Down) are jointly used. Finally [46] proposes a cost-aware caching strategy for ICN, comparing

it with non-cost aware strategies by means of numerical simulations.

In this context, network traffic measurement plays an important role in assessing the gains that caching technologies could bring to an Internet Service Provider (ISP), by e.g., estimating the attainable traffic reduction. A campus network is analysed in [47], in particular YouTube traffic, and the results of the measurements are then used to create a traffic generator. The traffic of over 20 000 residential DSL users is analyzed in [48], finding that Peer-to-Peer traffic is more cacheable than HTTP. [49] instead focuses on estimating the common measurement errors that can be incurred when analyzing HTTP traffic. [50] uses a real trace to show that pre-staging popular content directly on mobile phones could yield interesting bandwidth savings. Finally the already mentioned [32, 31, 30, 4] are also focused on traffic measurement and analysis.

2.2 Capture tools

Recent works on web caching within the radio mobile backhaul in New York metropolitan area [31] and in South Korea [32] have used proprietary tools satisfying the mentioned requirements. Unfortunately, none of these tools is publicly available; the first one is an internal capture tool from the operator, and the second, while developed by the authors of that paper, was not released publicly. Conversely, popular open source tools like *bro* [51] and *Tstat* [52] do not satisfy all the necessary requirements for our setup. Indeed *bro*, conceived as an intrusion detection system, is not suitable for high speed monitoring because it applies regular expressions on each packet to detect signatures of known threats, and therefore results to be very slow. *Tstat*, instead, is faster and accurate in analyzing TCP connections, but inaccurate in analyzing HTTP transactions. Consequently, both tools turn out to be not satisfactory for our needs.

For this reason, the analysis presented in this thesis is based on a novel tool, called HACkSAw, that we developed to accurately and continuously monitor web traffic in a modern operational ISP network, at any line rate, for any workload.

A comparison of the performance of the different tools, using the same one hour PCAP packet trace as benchmark, is reported in Tab.3.1, in chapter 3.

2.3 Datasets

Datasets of works inherent to caching or workload characterization can be request logs from servers, like [53, 54] which analyse the traffic logs from VoD services, or [24] as already described previously. They can otherwise be gathered via active crawling

techniques of popular portals, [55, 56] in particular analyze YouTube and compare its traffic to web or VoD traffic. Finally, datasets can be collected via passive measurement methodology [31, 32] as we do in this work.

A comparison of some basic information about the dataset considered in this and related work is given in Tab.3.2, in Chapter 3, where it can be seen that our datasets are not only the *longest in time* but also the *largest in volume* and the *smallest in population*. We therefore expect to gather statistically relevant results that additionally allow us to observe phenomena on timescale that were not observed in other studies focusing on shorter timescales and especially to get conservative estimate of caching gain in reason of the limited aggregation due to the small population size. Notice that Tab.3.2 additionally reports, for completeness, cacheability information collected in these studies; yet, the comparison is in this case only meant to be *qualitative*, as the dataset collection methodology, cacheability definition and analysis technique differ. It is however worth stressing that our cacheability results are in line with those gathered by [32], which is closest to this work in terms of methodology but radically different in terms of network environment.

2.4 Cacheability analysis

Since caching is a network primitive in most ICN systems (including CCN), most of the works on ICN perform some degree of cacheability analysis [23, 24, 25, 26][27, 28], although, as explained before, some perform simulations of very simple network topologies.

A common assumption to the evaluation of caching systems performance is to assume that content requests are generated under the IRM (Independent Reference Model[57], explained later in **??**), with a request distribution following a Zipf law. Considerable measurement efforts have been devoted to provide input to this workload in static settings, while very few consider the catalog dynamics over time. Characterization of video catalogs has especially attracted significant attention, from YouTube crawling [55], to measurement at a campus [47] or ISP [29, 30], just to cite a few. Focusing on YouTube traffic, [29], [30] show that IRM assumption may yield to a significant under-estimation of the achievable caching gains. However, the main focus of [30] is to propose a fine grained characterization of the data, rather than assessing the impact on the expected CCN gain (even a lower bound), as we do in this work.

Work closer to ours in terms of methodology is represented by [48, 49, 50, 32, 31, 24], which we described previously; in Sec. 5.1.2 we also provide a closer comparison between

the datasets used in those work and the ones used in this thesis. At high level it is worth remarking that while other works have measured cache performance for video applications [58], [48], most of the previous work has neglected web content which has, however, a significant impact on the amount of required storage to install in the network. Additionally, precise values of Web content *size* are often neglected in previous works, which are based on the analysis on HTTP requests only, neglecting all HTTP replies and resulting in possibly biased evaluations; the most notable exceptions are [31] and [32], which use a measurement methodology similar to ours and analyze either HTTP request and replies in radio mobile networks.

2.5 MapReduce frameworks

This work focus on the analysis of traffic cacheability properties in operational networks. As such this work provides input to the large body of work that focuses on many aspects of CDN/ICN caching, such as CDN/ICN comparison [24, 45] modeling and performance evaluation [33, 34, 35, 36], object replica discovery[37, 38, 39, 40, 42, 43, 44].

However, our goals are orthogonal with respect to the design and evaluation of new CDN/ICN techniques, so that we deem the above work out of scope. Rather, two very far apart classes of work relate to this: on the one hand, we have works whose focus is the monitoring and characterization of traffic cacheability statistics[47, 48, 49, 50, 32, 31, 30, 4]. On the other hand, we have works that employ big data frameworks[9, 10, 11, 12, 13, 14] for the purpose of traffic monitoring.

While our previous work [4] falls in the first category, this thesis is focused on the use of big data framework to scale up the analysis carried on in [4] for more limited datasets (i.e., in temporal, spatial and line-rate respects). See [4] for a more detailed comparison with the state of the art in this respect[47, 48, 49, 50, 32, 31, 30, 4].

Work that is closer to the contribution of this thesis is work using big-data frameworks for the analysis of network traffic or properties. From a high level viewpoint, large-scale data processing techniques can be divided into two classes. On the one hand, we have *stream processing* systems that operates over data nearly in real time: these includes both the general purpose systems (e.g. Storm, Spark) as well as systems specialized for the networking domain (e.g. Blockmon[9], DBStream[59]).

On the other hand, we have *batch processing* systems that operate over large datasets but are not suitable for real-time processing: a large family of these systems exists, which can be traced back to Google's MapReduce, that are surveyed in [60] and some of which (MapReduce[15], Stratosphere[11], Hama[12], Giraph[13], Graphlab[61]) are

experimentally compared in [62].

Map-Reduce is by far the most popular system in the networking community, and Apache Hadoop is the most popular among several alternative implementations. The range of networking tasks Map-Reduce has been used for include initial log analysis[15] to analyze of large social graphs such as Wikipedia[22]. There are instead fewer examples of work leveraging Hadoop MapReduce for the analysis of network traffic, which is thus closer to our work: [16] uses Hadoop to perform flow analysis, observing a very sizable speedup compared to non-parallel implementations; in [17] Hadoop and PIG are used together with R to scale up the analysis of a distributed monitoring infrastructure; [18] performs IP, HTTP and NetFlow analysis of several TB of traffic traces; MapReduce is used in [19] to process traffic traces of a live UMTS network in China; [20] uses a Hadoop framework to process large traffic traces to detect anomalies in the network; finally [21] uses MapReduce to perform botnet detection in a peer-to-peer network, with data obtained from a distributed sniffing system.

Chapter 3

Capture tool and dataset

Cacheability analysis of internet traffic is obviously only possible if it is possible to analyse actual traffic. The two obvious prerequisites are then access to an operational network and a probe to capture the traffic and extract in real-time the dataset to be processed later.

This chapter illustrates the network location where our probe is situated, the traffic analysis tool that runs on the probe, and the dataset it generates, which is then used to produce the results of the next chapters.

3.1 Network and capture points

We had the possibility to place our own hardware probe in a Central Office in the operational network of Orange in Paris. The network is laid out as in picture 3.1. The GPON (Gigabit Passive Optical Network) tree passively aggregates up to 64 users on a single optical link, up to 16 such links are then aggregated at the OLT (Optical Line Terminal), with a backhaul link towards the core.

In 2014 we were downstream of 2 such OLTs each with a 1Gbps backhaul, as expected we observed less than 2 000 users. In 2015 we moved one step up in the network, we were upstream of 2 full-duplex 10Gbps links, and downstream of a BAS (Broadband remote Access Server). The links aggregate several OLT backhaul links, where we observed more than 30 000 users. In both cases the packets captured were still encapsulated in PPPoE, and presented VLAN tags.

Due to the type of analysis performed, we need to guarantee that the routing of the packets is symmetric, because we need to capture both the upstream and downstream of each connection. Both locations where the probe was installed fulfilled this requirement,

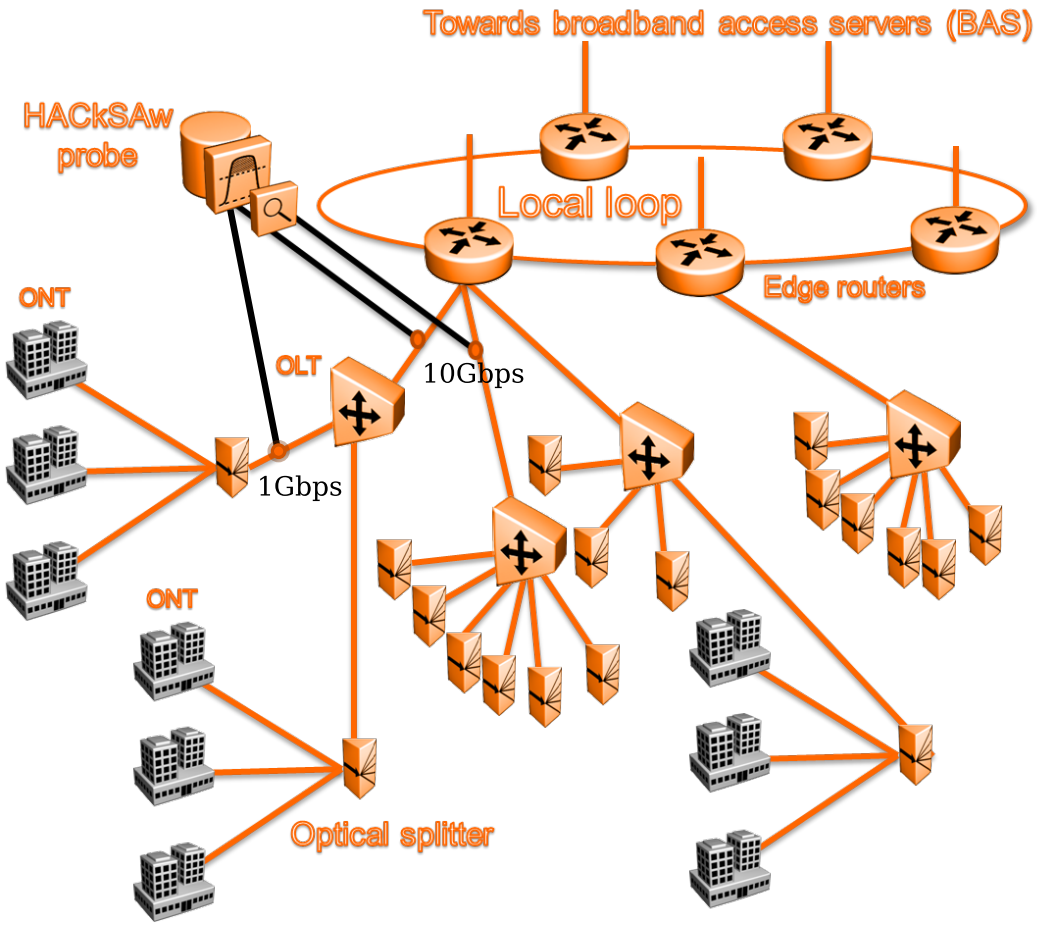


Figure 3.1: ISP network fiber access and back-haul. HACkSAw probes are deployed in different network positions (OLT vs ONT), corresponding to different link capacities (1Gbps vs 10Gbps) and levels of user aggregation (1,500 vs 40,000).

since they are the only links connecting the clients to the core of the network.

3.1.1 Hardware

The tool runs on an IBM server with 2 quad-core Intel Xeon E5-2643 CPUs at 3.30GHz with 48GB of RAM each, for a total of 96GB of RAM memory; thus it is a NUMA (Non Uniform Memory Access) setup. The server has 5 1-TB hard disks in a RAID-5 configuration, thus yielding 4TB of usable storage. Debian is the operating system installed.

The server is equipped with an Endace DAG 7.5G4 card (DAG 10X4-P for the 2015 datasets), capable of capturing packets from 4 links simultaneously, allowing us to

monitor 2 full-duplex Gigabit (10Gigabit for the 2015 datasets) links.

The capture cards of the probe were connected to passive optical splitters. A relatively slow speed link allows us to interact with the probe remotely.

3.2 HACkSAw, the capture tool

This section introduces HACkSAw, the live traffic analysis tool used in this work and other works[4] to produce the traffic traces. In particular, the following points will be addressed:

— motivations for writing a new tool, when many traffic analysis tools are already available.
— evolution in time of the requirements.
— general architecture of the system and its evolution to satisfy the requirements.
— some of the implementation details.
— performance of the tool.

3.2.1 Motivations

Traffic analysis is surely not a new thing, and therefore many tools exist to perform the task. Some tools match our needs better than others. As mentioned previously (§2.2), some tools were already adequate to our requirements, but those tools are not available, and other available tools, on the other hand, didn't meet our needs, therefore it was necessary for us to write a new tool.

3.2.2 Requirements

The requirements of the tool changed quite dramatically during the course of this PhD. Initially we only had PCAP traces of traffic, so the initial version of the tool was an off-line analyser; no timing issues, no hardware interaction. Since it used the PCAP APIs to access the packets from the trace file, it was rather trivial to extend it to support live capture. Some architectural modifications were necessary in order to achieve good live analysis performance at 1Gbps, some more radical changes were then needed to scale up the analysis to 10Gbps. Additionally, DNS analysis was deemed necessary. So in the end the final requirements for the capture tool are:

— Online and offline analysis. The tool must still be usable on offline traces, but its main focus has to be live capture.

— PCAP and DAG APIs. DAG APIs are fundamental to achieve line speed at high speed, whereas PCAP are needed because they are very widespread, and many other capture libraries provide compatibility layers for PCAP. By supporting PCAP it is this possible to support all the exising and future systems that offer such a compatibility layer.
— Not excessively big memory footprint. The probe should not be required to be equipped with huge amounts of memory, for cost, efficiency, and scalability reasons.
— HTTP and DNS analysis. We need an in-depth analysis of HTTP and DNS transactions, including timing information, object sizes, and other headers and information.
— Easy to maintain and extend. Ideally the design should be modular, in order to allow for easy maintenance and extension.
— 10Gbps to 40Gbps (or even 100Gbps) line speed capture without packet loss. The tool should be able to analyse the traffic in different points of the network at line speed, including close to the core.
— Proper software release for internal use: configure script, makefile, startup scripts to run the tool as a daemon.

3.2.3 Architecture and fundamental design choices

HACkSAw is written in C for 64-bit Linux systems. C++ was considered and discarded because of the added complexity and overhead. Any other language is unfit for the task, since we are dealing with time critical tasks and interacting with C APIs anyway.

On speed grounds all parsing of all layers is done in plain C, therefore including the Ethernet layer (including VLAN and PPPoE), TCP/UDP/IP, DNS and HTTP.

The behaviour of the tool can be configured both with commandline parameters and a configuration file. Appendix A contains a description of all the configuration options.

The output of the tool is a series of plain-text files, one for each protocol analyzed. Each line represents a connection or a transaction, values are separated by spaces or by tabs. This is indeed not the most space efficient way to represent this information, but we wanted

— human readable output, in order to be able to easily look at the raw data to perform basic correctness checks and help during debugging
— plain-text output, in order to be able to manipulate the results using standard

UNIX commandline utilities

— the minimum amount of complexity and overhead in the tool itself; compression is something that can be done externally (as we indeed do, see Chapter 5)

A complete description of the columns of each output file can be found in Appendix B.

The architecture of the tool evolved with time, the next two sections illustrate the first and the latest architectures that were actually used on live traffic to gather datasets and produce scientific results.

3.2.4 The initial version – 2×1Gbps

The first version of the tool was rather simple. Taking inspiration from [32], all TCP connections were reconstructed directly in main memory. Once the TCP connection was over, the reconstruction buffers were handed to the HTTP analyser. The PCAP API were used for capture, since they have a backend for the DAG cards used in our probe. Figure 3.2 shows a scheme of how the tool was structured.

Input

The PCAP APIs are not multithreaded, so a dispatching system was implemented to allow for multiple analyser threads in parallel. The producer thread receives each packet using the PCAP API, it analyses the packet superficially just enough to understand in which output bucket to copy the packet. To minimise the impact of locking between the producer thread and the worker threads, packets are grouped in batches of 1000 packets [1]. Once a batch is full, it is sent in a queue to the worker.

Processing

The workers themselves process the packets they receive from the batches, following and reconstructing the TCP session. After a few packets are received, the L7 protocol is detected. If the protocol is not supported, no further analysis is performed, the connection is marked so that no further reconstruction will happen, and the existing reconstruction buffers are freed. Once the TCP session has ended, or once it is inactive for too much time (by default 15 minutes, but it is configurable), the reconstructed buffers are handed to the HTTP analyser. The HTTP analyser, which runs in the same thread as the TCP analyser, analyses the full buffers, extracts all the relevant information regarding all the transactions and writes the relevant output in the log file.

1. the value can actually be configured at compile time

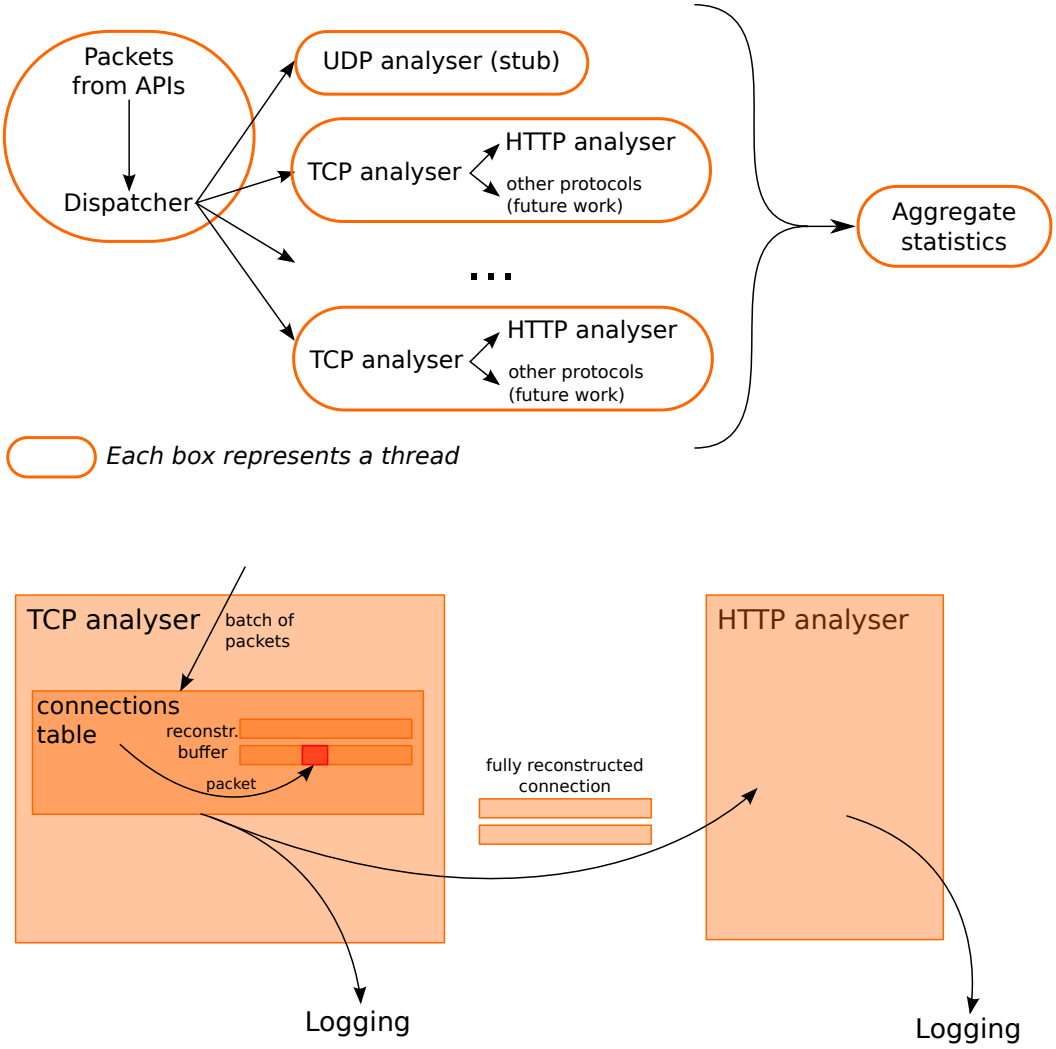


Figure 3.2: Diagram of operation of HACkSAw, first version.

The TCP threads need to periodically check for stale connections and terminate them. This causes periodic stalls in the threads which increase the latency, potentially stalling the producer thread. The queue of batches between the producer and the consumer threads exists to buffer those moments of higher CPU activity.

Output

Only two files were written: one for the TCP statistics, with one entry per TCP connection, and one for HTTP statistics, with one entry per HTTP transaction. Each entry is indeed timestamped, but only two files are created and appended to as needed.

Shortcomings

This implementation presented many shortcomings. The most evident one is that the producer thread (dispatcher) does not scale. It has to process and copy *every* packet received from the capture API. The processing overhead is minimal, the real bottleneck is copying the packet from the receive buffer to the packet queues. A small stopgap measure involves accepting only TCP packets and dropping every other packet early. This speeds up significantly the process at the expense of a negligible increase in the processing time. This was still not enough to scale up more than 14 Gbps.

The second huge problem is the incredible amount of memory needed. Since every HTTP connection was completely reconstructed in memory before being analysed, even small capture points with few users and little traffic used up all the 96GB of ram of the probe (and often spilling into swap, with catastrophic impact on performance)

A third shortcoming is that the output is not chunked in manageable chunks, and therefore the output files grow to unmanageable sizes. Performing most tasks on the output requires reading the whole file. When the file size in in the terabytes range, it is highly inefficient. Moreover it is not possible to selectively compress or transfer logs from previous days or hours.

3.2.5 The final version – 2×10Gbps and beyond

The final version addresses all the shortcomings of the first version, and furthermore adds some features to improve the maintenability and extensibility of the system. Figure 3.3 shows how the final version of the tool is structured.

Input

First of all, the DAG API is now used directly. This allows to use multiple hardware queues. The DAG card hashes the addresses and places the packet in the right queue, which is read by the consumer thread directly, thus removing the dispatcher from the picture. Without the bottleneck this design can now literally scale linearly with the number of CPUs. This solution was unfortunately not useful for us, as the address hashing does not work if the packets still have the PPPoE header. Another possibility is to dispatch the packets in the hardware queues based on the physical port on which they were received; this not only guarantees that both directions of any stream are assigned to the same thread, but additionally it also guarantees that correlated traffic is also assigned to the same thread. For example, using the hash of the IP addresses, it is possible that the DNS transaction used to resolve a name subsequently used to establish

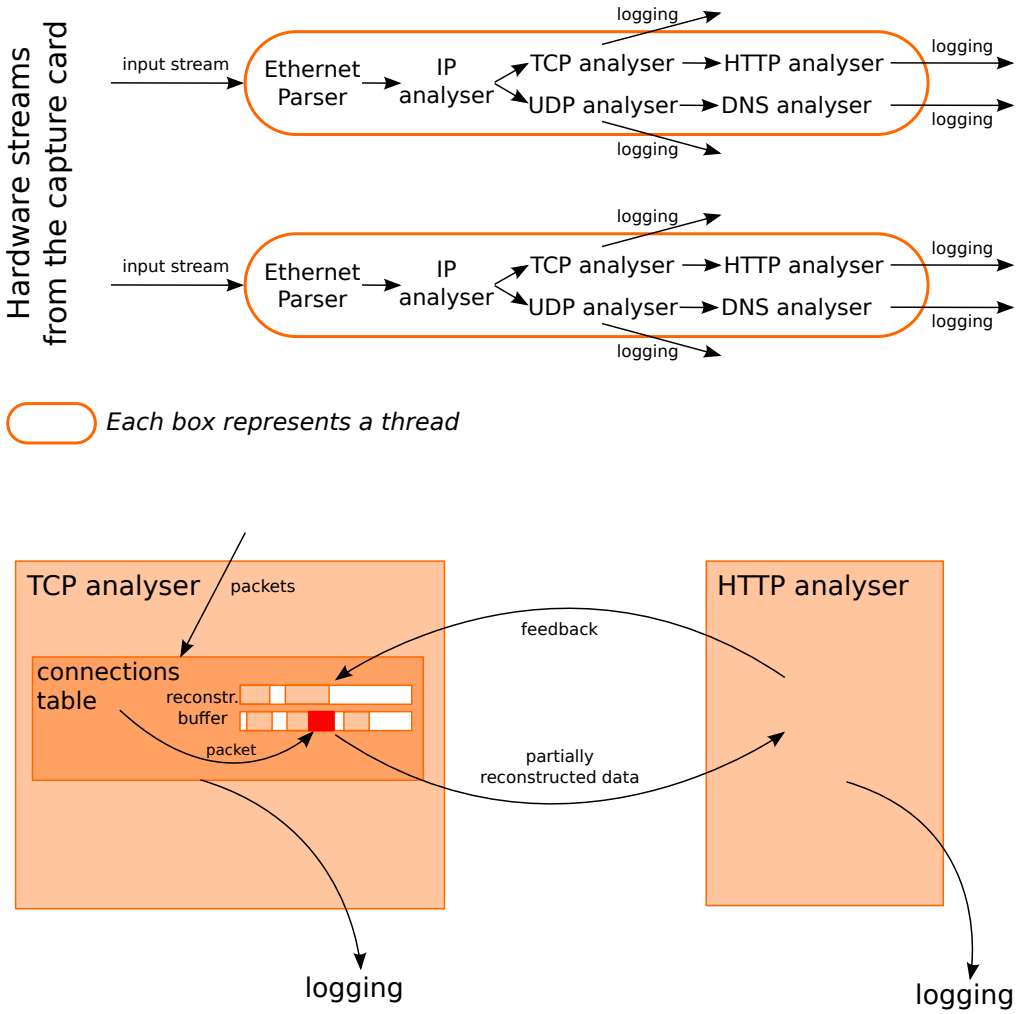


Figure 3.3: Diagram of operation of HACkSAw, final version.

an HTTP connection could be assigned to a different thread than the HTTP connection itself; dispatching packets based on hardware queues solves this problem.

The input API is now modular, and the input module can be set in the configuration file or in the commandline. There is one built-in module (`pcap_file`), and two more that are compiled if the relevant APIs are available (`dag` and `pcap`). The dispatcher bottleneck thread is still present when using the `pcap` input module. The `pcap_file` uses `mmap` to map the whole input file; the individual worker threads will then process all the packets and skip all the packets that are meant to be assigned to them.

There is now a clear internal API for input modules, so that adding new input

module literally only requires to add the new implementation in a new file and adding the implementation in the list of available inputs.

Processing

All supported layers (L3, L4 and L7) are now modular, with an internal API to detect the protocol and instantiate the right analyzer. This allows to easily implement and add new protocol analysers without having to perform changes spread out all over the place. Protocols can be enabled or disabled from the configuration file or from the commandline.

To reduce memory consumption and to increase processing speed, a new internal API was implemented to allow communication between the L4 and L7 layers. This system allows to only keep the data that will be needed, and allows to skip anything that is not needed. The process can be simplified as follows:

1. Packets are collected by the L4 analyser (e.g. an HTTP transaction)
2. The collected packets are handed to the L7 analyser
3. The L7 analyser can reply asking for more input (e.g. incomplete headers, return to point 1), or it can reply with a new target position in the stream (e.g. the headers were parsed, and we skip over the actual content of the object)
4. The L4 will discard all saved and incoming packets up to the new position; once a packet arrives at the new position, continue to point 1
5. The L4 will notify the L7 analyser when a packet was lost (if it wouldn't have been discarded anyway)
6. The L7 tries to handle the situation anyway, in case of success, return to point 3 (e.g. if the lost packet was not important, or maybe the L7 protocol analyser can cope with lost packets)
7. In case of failure, the L7 returns a failure code that causes the L4 to drop all saved packets and skip all subsequent incoming packets (thus never calling the L7 again)
8. The end of the stream is handled like a packet loss

All this complex interaction is implemented with only 2 functions per direction (so 4 in total). The semantic of those functions can be summarized as:

— L7 should process this data and tell the new target offset to L4.

— L7 should process this data and tell the new target offset to L4, but if the new offset is smaller than the offset where the packet was lost, L4 will set the new target offset anyway, discarding potentially important data.

Output

The output is also modular. The default (and so far only) output module is the plaintext module, but other output modules (e.g. binary, database, hadoop) are easy to implement and add.

The plaintext module now splits each output file in chunks of configurable size. For example, it is possible to have the logs chunked by day or by hour. This allows to transfer, compress, and process specific time intervals, even while the software itself is still runninng.

The plaintext module has also an increased buffer size, thus reducing the number of system calls to be performed. Writing to disk thousands of times per second has a negative impact; decreasing the amount of system calls and filesystem operations by one or two orders of magnitude definitely has a positive impact on performance.

Advantages

First of all, removing the bottleneck allows to scale up linearly with the number of available CPUs. The complex stateful system of L4/L7 analysers allows to discard all unneeded packets, thus speeding up even more. The increased output buffer mitigates the impact of performing system calls, which was not a dominant factor, but it still contributes to improve the overall performance.

3.2.6 Some implementation details

Hash function for the dispatcher

All hash functions are applied to the XOR of the source and destination IP addresses. This guarantees that both directions of the stream are assigned to the same worker.

Several hash functions were tried for the dispatcher thread. The first implementation used a FNV-1a hash of the XOR of the source and destination IP address. Source and destination ports were not taken in consideration because they added undue complexity to the dispatcher thread. Since the dispatcher thread is the bottleneck of the architecture, it is important that the least amount of work be performed on the critical path.

Some tests showed that using just the XOR of the least significant bytes of the source and destination IP addresses was just as good, so that is the hash function used now when the PCAP APIs are used.

Slab allocator

Memory is allocated and deallocated quite often in the analyser threads, and this puts a lot of pressure on the memory allocator. The standard allocator does a rather good job in general, but its performances can be improved upon, by implementing and using purpose-taylored allocators.

The logic behind the custom allocator is actually rather simple. Each thread has its own independent allocator. Each allocator keeps a list of free memory chunks (called *free list*) for a range of sizes that is used often in the program. When an allocation is performed, the first free item is removed from the right free list and returned; conversely when a memory area is freed, it is placed back on the head of the correct list. When a list is empty, a big chunk of memory is allocated using the standard allocator, subdivided in chunks of the right size, which are then placed in the appropriate free list.

The main advantages are two. The first is a decreased memory usage, because the custom slab allocator does not keep any additional management structure for each allocation; this also implies a reduction in CPU usage, as there are fewer memory structures to update during memory operations. The second is that, since we have one independent allocator per thread, there is no lock contention during allocations; this also contributes to reduce the CPU usage.

Of course there are also disadvantages. First of all, the allocator must be told the size of the memory chunk when freeing, in order to put it back in the right free list. This is an implementation detail, but passing the wrong value when freeing will have catastrophic results, which result in very elusive bugs. Another disadvantage is that the standard system libraries have some built-in checks to catch some possible memory corruption issues, which are of course absent in the custom slab allocator. And finally, tools like Valgrind[63] will not work with custom allocators. It can be seen that all the disadvantages concern development and debugging, so to help debugging the slab allocator can be disabled at compile time.

The end result is that with the custom slab allocator there is roughly a 10% increase in the performance combined with a 10% reduction in memory consumption.

Table 3.1: Comparison of Bro, Tstat and HACkSAw. The best values for each column are in bold.

Tool	**Detected requests**	**CPU [sec]**	**RAM [GB]**	**Replies w/o size**	**Relevant replies**
Tstat	2 531 210	445	**0.3**	1 128 109	1 403 101
bro	**2 559 056**	8033	4.2	424 355	**2 134 701**
HACkSAw 0.2	2 426 391	368	5.8	328 465	2 097 926
HACkSAw 0.4	2 393 514	**235**	**0.3**	**269 311**	2 124 203

3.2.7 Performance

The final version of the tool can safely process 2 full-duplex 10Gpbs links for months with 2 cores and 20GB of RAM, when using DAG capture cards.

A comparison of the performance of the different tools is reported in Tab.3.1, using the same one hour PCAP packet trace as benchmark. The table's columns report, respectively: the number of distinct HTTP requests; the total CPU time, cumulated across threads; the total amount of RAM used; the number of detected requests without a size; the number of detected requests with a size.

HACkSAw version 0.2 was used to capture the first trace, while the much-improved version 0.4 was used to capture the second trace.

All tools detect approximately the same amount of requests; *bro* uses 10 times more memory and runs over 20 times slower than *Tstat*, whereas HACkSAw manages to be almost as accurate as *bro*, and as fast as *Tstat*. *Tstat* catches most of the transactions though it fails to match requests with the replies, and it fails to report the size of the object (at least when the Content-Length header is not within the first IP packet of the reply, which happens more than 30% of the cases in our benchmark). HACkSAw v.0.4 is the fastest and arguably very accurate, since it collects almost all the full transactions.

In the latest location, with 2 full-duplex 10Gigabit links, HACkSAw is using only 2 cores of the 8 available. Per-core CPU usage varies from 35% during off-peak hours to 60% during peak hours. Total memory consumption stays under 20GB (thus 10GB per thread) after 2 weeks of analysis. The disk bandwidth to write the output logs is less than 1.5MB/s per thread. With our current hardware and additional capture cards we estimate that we could probably scale up to 4 or maybe even 8 full duplex 10Gbps links.

3.3 Datasets

This section introduces the datasets collected using the tool, the statistics collected in the dataset, and some details on the dataset itself.

3.3.1 Statistics collected and overview

The tool collects many details about the TCP, UDP, HTTP and DNS transactions. The statistics used to compute cacheability are introduced here, for a full detailed list of all the collected statistics, see Appendix B.

Each detected HTTP request/reply transaction is recorded with a number of fields and associated statistics: time-stamp, user ID, object ID, Content-Length[64], actual transaction length over the wire, and range information due to HTTP `Range` requests.

The time-stamp is used for time-correlation and timeslot binning and it is in the Unix time format (number of seconds since January 1st 1970) with microsecond accuracy.

The user ID is the MAC address of the home router of the customer. Since customers get new IP addresses each time the home router reconnects, we needed a more stable identifier, and customers very rarely change their home router. For privacy reasons we actually used a salted hash of the MAC address.

The Object ID is the full URL of the requested object, concatenated with the ETAG header, if present. The ETAG is a header optionally returned with the reply, and it is used to indicate whether a given object has changed or not. It consists of a string, usually some kind of timestamp; equal values of ETAG for the same object indicate that the object hasn't changed in time. The ETAG is important for objects that change very frequently in time, like the front page of a news website. The final result is then hashed, both for efficiency reasons, since a 64 bit value is easier to handle than a potentially very long variable length string, and for privacy reasons, since URLs may contain sensitive information.

The Content-Length field is the object length optionally, but very frequently, advertised in the HTTP reply. In case of Range requests, the Content-Length is the length of the requested range, and not the whole object. In Chapter 5 we use this field to further disambiguate between different objects with the same URL.

The effective length is the number of bytes really transmitted on the wire. In most cases it is the same value as the Content-Length, but in case of interrupted or aborted downloads it will be a smaller value. This value is always present, but can be zero in case no content was transferred, like in case of redirects or errors.

The range information is used in Chapter 5 to properly reconstruct the size and

amount of bytes transferred by separate Range requests for the same object, which are very common in video and audio streaming. The range information indicates the first and last byte of the requested range, and the total length of the object. This is the only place where the total object size is indicated in case of Range requests, since the Content-Length will be the size of the requested range (e.g. $last - first + 1$),

3.3.2 The datasets

Our methodology is based on deep packet inspection (DPI) of the HTTP protocol and therefore it does not apply to HTTPs, where all bytes transferred across a TCP connection are encrypted. We observed 15% of HTTPs web traffic in the first dataset, and 30% in the second; this statistic is expected to grow in the future, as HTTP 2.0 specifies encryption by default. In order to measure the amount of HTTPs traffic, we simply measured the amount of bytes transferred over ports 80 for HTTP and 443 for HTTPS. This is not a perfectly accurate way of measuring, because we are intentionally ignoring traffic on non-standard ports, but here we are not interested in an overly accurate figure, we only want to assess if the amount of unecrypted traffic is still a significant portion of the total traffic.

Considering the highly predominant usage of HTTP over HTTPs in our dataset, the results presented in this thesis are valuable to draw significant conclusions regarding cache performance at the network edge.

We collected several datasets, the ones used for scientific purposes are:

— the first one (`2014`) spans 42 days, from April 18th to May 30th 2014

— the second one (`2015-1`) spans 30 days, from January 10th to February 9th 2015

— the third one (`2015-6`) spans from June 11th to November 23th 2015, with two interruptions, for a total of 132 days.

Tab.3.2 reports a summary of these datasets in terms of the average daily and total number of objects and clients, comparing them to other datasets from other related works.

As indicated above in 3.1, the first dataset was collected in the edgemost location of the network, right above the OLT. The users are exclusively ADSL customers. The other two datasets were collected one step closer to the core, just below a DSLAM.

Table 3.2 shows a comparison of our datasets with the most notable datasets used in literature; the largest values are shown in bold, for our datasets a daily average is also presented.

Our first dataset has a very small user fanout (less than 2000 users), due to the

Table 3.2: Comparison of the datasets in this and related works. The largest values for each column are highlighted in bold.

Reference	Length	Clients	Requests	Distinct objects	HTTP traffic	Savings requests	Savings traffic
2015-6	**132 days**	40k	**26.3G**	**8.9G**	**3.2PB**	52%	31%
daily average	-	*22k*	*194M*	*90.9M*	*23TB*		
2015-1[?]	30 days	30k	6.6G	2.5G	575TB	53%	40%
daily average	-	*24.5k*	*220M*	*102M*	*19TB*		
2014[4]	42 days	1.5k	369M	174M	37TB	42%	35%
daily average	-	*1.2k*	*8.6M*	*5M*	*881GB*		
[48]	14 days	20k	–	–	40TB	16–71%	9.5–28%
[49]	14 days	20k	–	–	42TB	–	–
[50]	1 day	200k	48M	7M	0.7TB	10–20%	13–40%
[32]	8 days	**1.8M**	7.7G	–	248TB	54%	41%
[31]	1 day		42M	–	12TB	16%	7%
[24]	1 day	–	6M	–	–	–	–

positioning at the very edge of the network. This allows us to assess the effectiveness of a cache even with a small amount of distinct clients. Our second and third dataset have more typical user fanouts. Still, we do not come anywhere near [32], since that dataset was collected in the core, while we are positioned at the edge, inside the access network.

From a length perspective, our datasets are by far the longest. The third one, in particular, spans over 4 months. Such a long dataset allows us to observe the evolution of the cacheability and traffic reduction statistics in time over a long timespan; as we will illustrate in the next chapters, we observe a rather stable trend.

The sizes of the datasets themselves are huge, considering number of requests, number of objects and total amount of traffic. The sheer size of the datasets is both an advantage and a curse. A huge dataset will in general provide more credibility to any statistic calculated from it, with the downside of having to perform computations on extremely huge amounts of data. Our third dataset in particular is bigger than any of the other ones we observed in literature.

Also just considering the volume of the HTTP traffic, we can see that the the first dataset is on par with most other datasets, the second is twice as big as the next biggest one, and the third, with $3.2PB$, dwarfs all the other datasets combined. The sheer size of our datasets posed a huge scalability problem for us; analysing all that information, especially the third dataset, forced us to look into big data solutions, as explained later in Chapter 5.

It is important to notice that the cacheability statistics in all our datasets are consistent, both with themselves and with the datasets used in literature.

Chapter 4

Cacheability analysis of real traffic

A common assumption to the evaluation of caching systems performance is to assume that content requests are generated under the IRM (Independent Reference Model), with a content popularity distribution following a Zipf law. The IRM considers all interactions independently from each other, therefore it completely disregards the temporal correlation between the requests.

Considerable measurement efforts have been devoted to provide input to this workload in static settings, while very few consider the catalog dynamics over time. Characterization of video catalogs has especially attracted significant attention, from YouTube crawling [55], to measurement at a campus [47] or ISP [29, 30], which show that IRM assumption may yield to a significant under-estimation of the achievable caching gains.

In this chapter we will introduce the statistics and metrics used in this thesis. The statistics all refer to a time interval, so after introducing the statistics we will perform some timescale analysis to find reasonable time intervals to calculate the statistics on. The statistics will then be used to estimate the size of real caches, and LRU cache simulations are then performed using the estimated cache sizes. We will see that a sizable share of traffic can potentially be cached.

4.1 Key Statistics

We now introduce the statistics that will be used throughout this thesis. They are all applicable on a time interval, and provide some metric (an upper bound) of the amount of traffic or requests that can be cached. Figure 4.1 provides a visual representation.

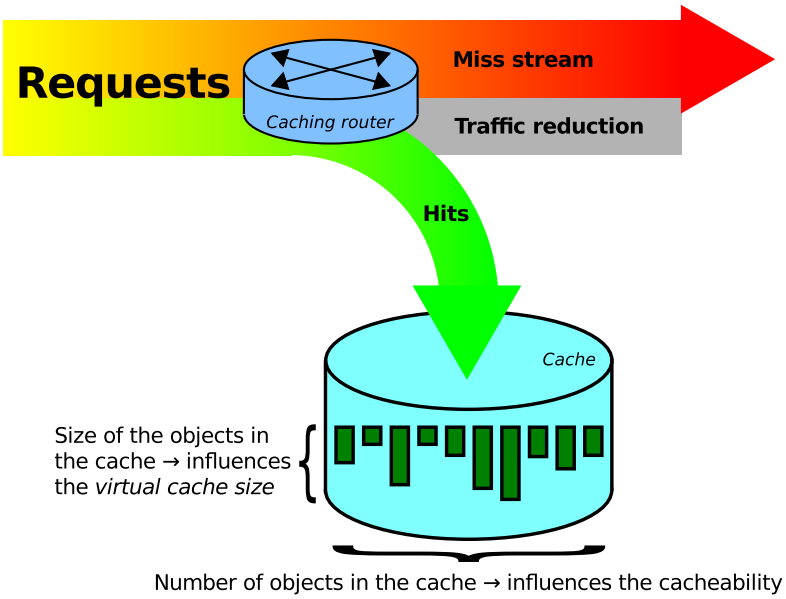


Figure 4.1: Illustration of the analytics associated to ISP caching: *object cacheability*, *traffic reduction* and *virtual cache size*.

Let us define as *catalog* C the set of distinct objects requested in a given time interval, and denote with $N_o = |C|$ its size in terms of the number of distinct objects. While we do not make any assumption, we remark that the catalog is generally very large and rather typically most of those objects are requested only once in the time interval.

We now define as *cacheability* the fraction of requests for objects (or parts thereof) requested more than once in a given time interval. This index is fairly commonly used [48, 65, 66, 4] to find the upper bound of the expected benefits of reactive caching. While the first request of an object is not considered cacheable [1], whereas all its subsequent requests in the same time interval are. Specifically, cacheability is an upper bound since deterministically assuming all subsequent request to generate a hit implicitly assumes the cache to be large enough to avoid content eviction due to cache size limit. Considering for the time being full-object requests for the sake of simplicity, and denoting with N_{hits} the number of potential cache hits, N_r is the number of requests observed in the given time interval, and N_o the catalog size defined above, cacheability can be defined as:

$$\frac{N_{hits}}{N_r} = \frac{N_r - N_o}{N_r} = 1 - \frac{N_o}{N_r}$$

1. It would generate a cache hit in case proactive prefetching, as opposite to reactive caching settings considered here

Notice that cacheability is an object-wise metric: we also need a byte-wise metric that explicitly takes into account the volume of objects. It's in fact possible that small objects are more cacheable than bigger objects (and we will show later in 5.3 that this is indeed the case), so it is also important to estimate the actual amount of traffic potentially saved by caching. We therefore define *traffic reduction* as an index measuring the maximum amount of traffic that can be potentially saved across a link over a given time interval as a consequence of content cacheability. Denoting with R the total traffic, with R_u the uncacheable traffic, and R_c the cacheable traffic (all measured in bytes), traffic reduction can be defined as:

$$\frac{R_c}{R} = \frac{R - R_u}{R} = 1 - \frac{R_u}{R}$$

Finally, we observe that cacheability and traffic reductions are an *upper bound* of the achievable performance. We therefore need an estimate of the cache size required to achieve such performance, and denote this index as *virtual cache size*. We observe that, in case the arrival process would strictly order all requests for the same content (i.e. all requests for an object i arrive in sequence before requests for object $i + 1$) then the virtual cache size would simple amount to the largest object in the catalog. This estimate is however very optimistic, so that we prefer a conservative approach that provides an upper-bound to the cache size: this bound is suitable when requests for all objects are intermingled, so that there is no temporal correlation between requests (i.e. requests arrive in random order with a rate proportional to the popularity of each object in the catalog). In this latter case, the *virtual cache size* is defined as the sum of the observed size V_o of the cacheable objects o:

$$\sum_{o \in cacheable objects} V_o$$

where cacheable means that the object o has been seen at least twice in the timeslot and the size V_o is the number of distinct bytes of content observed for the object o.

Notice that these statistics are relative to a specific timeslot, and timeslots are independent. So slicing the traces in timeslots disregards the temporal locality of requests across timeslot boundaries. That's also why finding the optimal timeslot size is important.

4.2 Timescale analysis and content popularity

Traffic characterization is an essential prerequisite of traffic engineering. Network dimensioning and upgrading lie upon the knowledge of the relation between three entities: traffic demand, network capacity and quality of service. What makes traffic characterization a difficult task is the stochastic nature of Internet traffic, complex to synthesize via simple models.

In literature, a wide range of models exists, varying model abstraction and related complexity according to a more microscopic or macroscopic analysis of network dynamics. In this thesis we avoid a detailed representation of a network of caches, which turns out to be very difficult to represent analyticallyeven for a tandem cache and simple workloads [67, 68, 69]. We rather prefer a simplified characterization of web traffic, based on key system properties and applicable to general in-network caching systems. Such model abstraction, assuming an independent reference model (IRM), might be leveraged for the dimensioning of a micro CDN. The key factors impacting the performance of an in-network caching system and that our model takes into account are:

— the timescale at which content popularity may be approximated by an independent reference model (IRM) (Sec.4.2.1);

— the content popularity at the given timescale (Sec.4.2.2).

From this characterization, we later infer in Sec.4.3.2 the minimum useful amount of memory to embed in the home network and in edge routers in the micro CDN architecture.

4.2.1 Timescale analysis

Before presenting observations from the network probe, we use a simple explanatory model to show that measuring content popularity at a timescale where the IRM assumption does not hold may lead to wrong predictions in terms of memory requirements (e.g. over a large time window).

We divide the time axis in windows of size $T > 0$, $W_i = [iT, iT + T)$, and assume that, in each time window W_i, objects in content catalog A_i are requested following a Poisson process of rate λ, with $A_i \cap A_j = \emptyset$ for all $i, j : i \neq j$. The average object size is σ bytes. A_i is Zipf distributed with parameters α, N, i.e. a content item of rank k is requested with probability $q_k = ck^{-\alpha}$, $k \in \{1, \ldots, N\}$, $|A_i| = N$.

By using the modeling framework developed in [27] for an LRU cache of size x in bytes, we know that if $T >> x^\alpha g$, with $1/g = \lambda c \sigma^\alpha \Gamma(1-1/\alpha)^\alpha$ the cache miss probability for an object of rank k tends to $\exp\{-\lambda q_k g x^\alpha\}$.

However, if one estimates the content popularity as the time average across m contiguous time windows, the estimated miss probability would be $\exp\{-\lambda q_k g(x/m)^\alpha\}$. Indeed, the right cache performance measured across m contiguous time windows of size T is still $\exp\{-\lambda q_k g x^\alpha\}$ resulting in an overestimation factor m of the required memory, for the same miss ratio.

In this section we estimate the timescale over which the IRM model can be used to estimate cache performance without using complex measurement-based models, e.g. [29],[30].

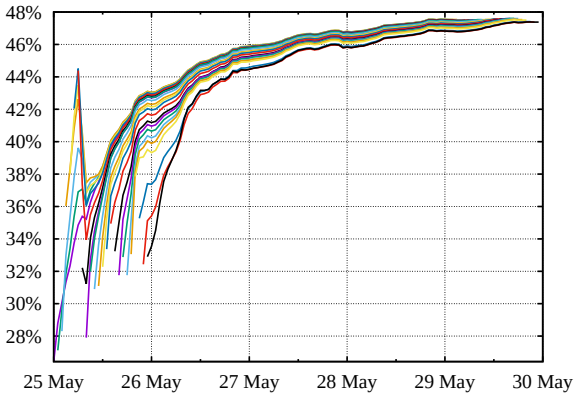
Observation 4.2.1. *In order to exploit a IRM cache network model for system dimensioning, one needs to estimate the smallest timescale, referred to as "cutoff" timescale at which the IRM assumption holds. As a consequence, above the cutoff timescale, every new content request gives a negligible contribution to catalog inference.*

In Fig.4.2(a),(b) we plot cacheability and traffic reduction as computed over our dataset at different time windows: from one hour to an entire contiguous week at incremental steps of one hour. The statistics are also computed starting at different time instants, delayed by one hour each. We observe that the two statistics have a cutoff scale above which they reach a plateau. In Fig.4.2(c), we report the time required for the cacheability to attain percentiles (namely, the 75%, 90%, 95% and 99%) of the long term value: it can be seen that 90% of the traffic reduction are attained in less than 24 hours, irrespectively of the start time.

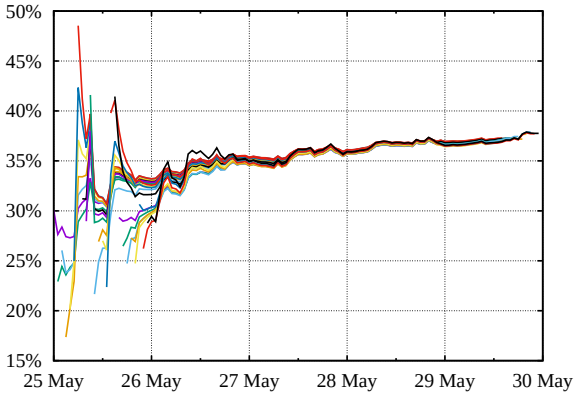
Observation 4.2.2. *The cutoff scale is hard to be measured as it changes on a daily basis as a function of many factors that cannot be rigorously quantified. However, we observe that for practical purposes aggregate web traffic would benefit from caching no more than a daily content catalog.*

In Fig.4.2(a),(b) we also observe that the cacheability stabilizes at about 47% while traffic reduction amounts to almost 37%. These values provide a first rough estimation of the opportunities to cache data currently available within the ISP network at relatively low user fan-out. While the statistics just presented provide insights on the potential gains achievable by caching a daily content catalog, we now investigate temporal evolution of the catalog.

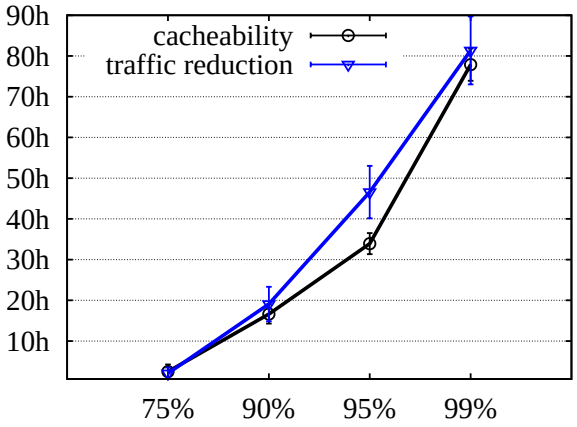
To this aim, we introduce a measure of auto similarity based on the *Jaccard coefficient*, that indicates the proportion of objects in common between two given sets: $J(A,B) = \frac{|A \cap B|}{|A \cup B|}$ (If $A = B = \emptyset$ then $J(A,B) \triangleq 1$. Clearly, $0 \leq J(A,B) \leq 1$. We then



(a)



(b)



(c)

Figure 4.2: Cumulative cacheability (a) and traffic reduction (b), starting from different hours and for various timespans. (c) Hours needed to reach some percentiles of the cacheability and traffic reduction plateaus, with standard deviations.

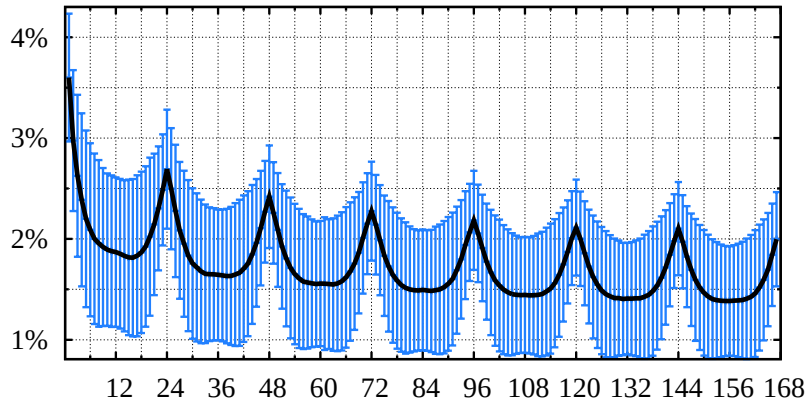


Figure 4.3: Jaccard auto correlation function $\mathcal{R}_{\Delta T}(k)$.

define the Jaccard auto correlation function as

$$\mathcal{R}_{\Delta T}(k) = \frac{1}{n} \sum_{i,j:|i-j|=k}^{n} J(C_{i\Delta T}, C_{j\Delta T})$$

being $C_{i\Delta T}$ the content catalog measured over the time window $i\Delta T$. Fig.4.3 shows $\mathcal{R}_{\Delta T}(k)$ for $k = \{0, \ldots, 168\}$, $\Delta T = 1$hour, during one working week in May 2014 (showing standard deviation as error bars). An interesting conclusion can be drawn.

Observation 4.2.3. *The catalog is weakly auto-correlated, as $\mathcal{R}_{\Delta T}(k)$ falls from 100% to less than 5% and it completely regenerates asymptotically, as $\mathcal{R}_{\Delta T}(k) \to 0$ when $k \to \infty$. A periodic component with period of about 24 hours is also present as a result of users' daily routine.*

Finally, we show that the catalog exhibits a night/day effect. Fig.4.4 reports $J(C_{k_0\Delta T}, C_{(k_0+k)\Delta T})$, with $\Delta T = 1$hour and $k_0 < k \leq 72$, for multiple $k_0 = \{0, 2, 4, 6, 8\}$. The figure shows that the catalog has different properties during off peak hours ($k_0 = \{0, 2, 4\}$) than peak hours ($k_0 = \{6, 8\}$). Off-peak hours are characterized by content items that unlikely appears again in the future, while on-peak content items show periodic components of 24 hours.

4.2.2 Content popularity estimation

According to previous observations, the timescale of interest turns out to be approximately defined by removing the night period, i.e. the off peak phase. This may be a complex task as the off peak phase changes on a daily basis. Nevertheless, we observe that the off peak phase has statistically weak impact on the overall distribution as it

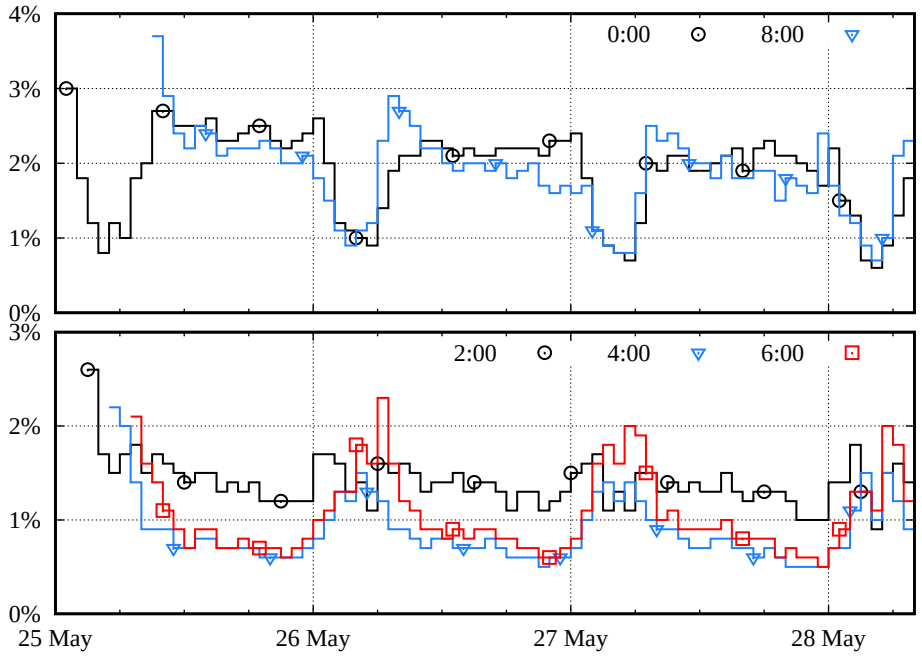


Figure 4.4: Jaccard coefficient, $J(C_{k_0\Delta T}, C_{(k_0+k)\Delta T})$, $k_0 = 0, 2, 4, 6, 8$.

carries samples in the tail of the popularity distribution at low rate, so that 24 hours can be used as good approximation timescale. We now present a model of content popularity estimated over 24 hours.

We test the empirical popularity against various models and find the discrete Weibull to be the best fit with shape around 0.24 (long tailed). In Fig.4.5, we report the empirical popularity distribution with corresponding 95% confidence bands (see [70] for similar analysis). We also plot, in red, the model fit to the available sample with 95% confidence bands. By means of extensive tests on this model we assess accuracy over all 24 hours samples on our data set. It follows that (i) for the *tail* of the distribution, a simple discrete Weibull passes a χ^2 goodness of fit test [71], with p-values exceeding 5% significance level, (ii) the good model for the *entire distribution* turns out to be trimodal with three components: a discrete Weibull for the *head* of the distribution, a Zipf for the *waist* and,

a Weibull again for the *tail*, i.e. $f(k) =$

$$\begin{cases} \phi_1 \dfrac{\beta_1}{\lambda_1}\left(\dfrac{k}{\lambda_1}\right)^{\beta_1-1} e^{-(k/\lambda_1)^{\beta_1}} & k < k_1 \\ \dfrac{\phi_2}{k^{\alpha_2}} & k \in [k_1, k_2] \\ \phi_3 \dfrac{\beta_3}{\lambda_3}\left(\dfrac{k}{\lambda_3}\right)^{\beta_3-1} e^{-(k/\lambda_3)^{\beta_3}} & k > k_2 \end{cases}$$

with parameters $\lambda_1, \beta_1, \alpha_2, \lambda_3, \beta_3, \phi_1, \phi_2, \phi_3 \in \mathbb{R}^+$; $k_1, k_2 \in \mathbb{N}$. The parameters have been estimated by using standard maximum likelihood (ML) applied to the piecewise function $f(k)$. The set of parameters of each piece of $f(k)$ is estimated independently to the others in order to fix the shapes exponents $\beta_1, \alpha_2, \beta_3$ and the scale factors λ_1, λ_3. An ML estimator is not available for the entire distribution and we therefore use the method of moments to determine ϕ_1, ϕ_2, ϕ_3. The procedure can be iterated to obtain a better estimation by running ML first and MM afterwards. In our samples after four iterations the parameters stabilize to stationary values that we have reported for one day in Fig.4.5 where $\beta_1 = 0.5$, $\alpha_2 = 0.83$, $\beta_3 = 0.24$.

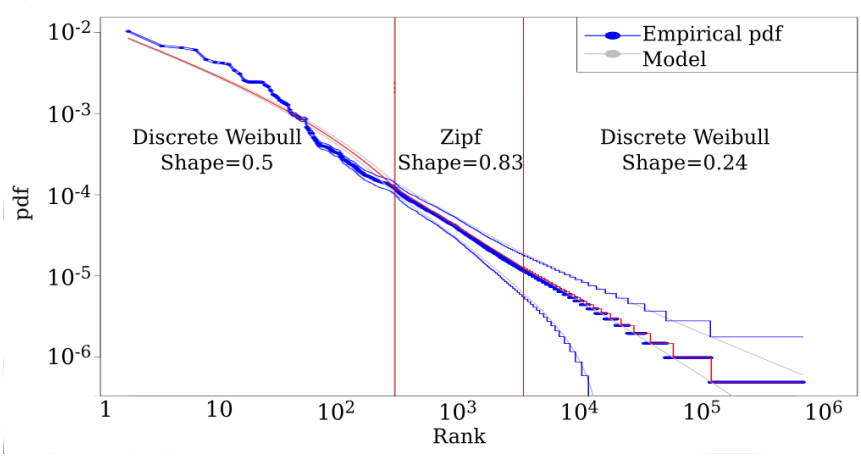


Figure 4.5: Empirical web content popularity and model fitting with corresponding confidence bands.

It is not uncommon to confuse a heavy-tailed distributions (e.g. Zipf) with a long-tailed one (e.g. Weibull). The most naive techniques based on the analysis of the linear regression of the loglog plots are known to be error prone. More powerful techniques to analyze extreme values of a distribution are based on the use of the Hill statistics [**?**],[**?**]. It is possible to build a hypothesis test based on the Hill statistic $H_n = 1/k \sum_1^k \log \frac{X_{(i)}}{X_{(k+1)}})$

for $k = 1, \ldots, n-1$ being n the size of the sample and $\{X_{(i)}\}$ the ordered sample. The null hypothesis is $H_n \to \alpha$ to identify a Zipf tail and $H_n \to 0$ to identify a Weibull tail (see [**?**]). We have applied the test based on the Hill statistic on the popularity function of a month of data and we have found that the test $H_n \to \alpha$ is always rejected. The test $H_n \to 0$ is however never rejected. In Fig.4.6 we report the Hill statistic for three data samples: one is composed of quantiles simulated from a Zipf distribution with shape equal to 0.83 (a recurrent value in the literature that our analysis attributes only to the waist of the distribution, see Fig.4.5); the second sample is obtained by simulating a discrete Weibull distribution with shape equal to 0.24 (as obtained from our data). The third sample reported in the figure is obtained from our network measurements. All samples have the same size. From Fig.4.6 we observe the convergence properties of the different Hill statistics that would exclude a Zipf tail for content popularity.

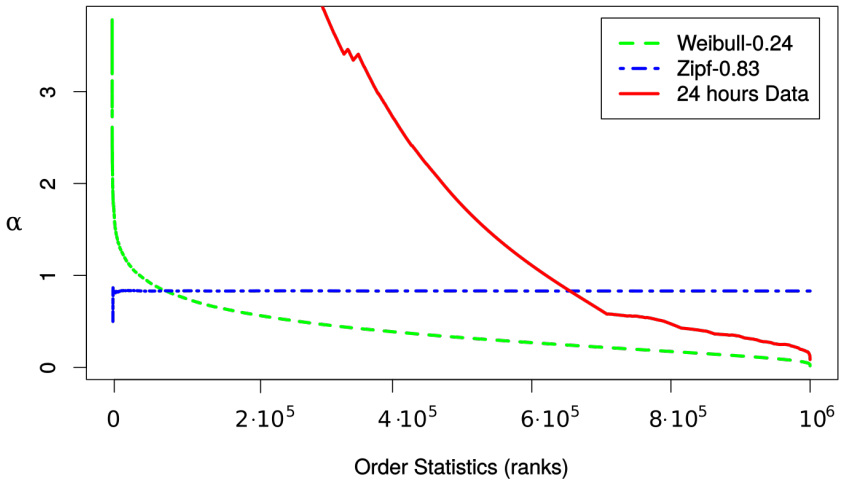


Figure 4.6: Hill plots comparison: Zipf-0.83, Weibull-0.24 and a 24 hours sample of data.

Interesting conclusions can be drawn from our popularity characterization. In literature, the majority of analytical models assume a Zipf distribution with shape $\alpha < 1$ for the entire distribution. Remark that, if the same Zipf law characterizing the waist is prolonged all over the support of the distribution, a finite support, corresponding to a content catalog estimation, must be imposed. We recall that the miss probability of a cache of size x employing the LFU replacement policy is given by $m(x) = P\{R > x\} = 1 - \sum_{k=1}^{x} q_k$. If we assume Zipf popularity with shape $\alpha < 1$ than $m(x) = 1 - (x/N)^{1-\alpha}$. If we assume Zipf popularity with shape $\alpha > 1$ than $m(x) \sim x^{1-\alpha}$. For a Weibull distribution $m(x) = e^{(x/\lambda)^{\beta}}$.

Cache performance would then depend on the ratio between cache and content catalog size, while it is a function of cache size only under the more precise Weibull tail fit that we made. Moreover, the cardinality of the catalog, N, is estimated with unbounded confidence intervals (see Fig.4.5), whereas all Weibull's parameters can be estimated with arbitrary low error, by increasing the size of the sample. As a consequence, an over-estimation of the catalog size by a given factor under the all-Zipf model would lead to memory over-sizing of the same factor for a given target miss ratio. Conversely, the miss ratio under Weibull requests [72], e.g. of an LRU cache, can be estimated with arbitrary precision by increasing the size of the sample to estimate the popularity law. Hence, we derive the following.

Observation 4.2.4. *Accurate content popularity characterization is fundamental to drive a correct cache system dimensioning. Approximate models based on (i) all-Zipf assumption, (ii) possibly fit over long time scales, coupled to (iii) IRM model assumptions, may lead to excessively conservative results, and ultimately to misguided system design choices.*

4.3 Simulations

In the following, we present some statistics and some realistic simulations driven by our dataset. The goal is to (i) evaluate the amount of memory required within the backhaul to absorb cacheable traffic and (ii) to assess the accuracy of the model introduced in previous section for the dimensioning of a micro CDN system.

4.3.1 Scenarios

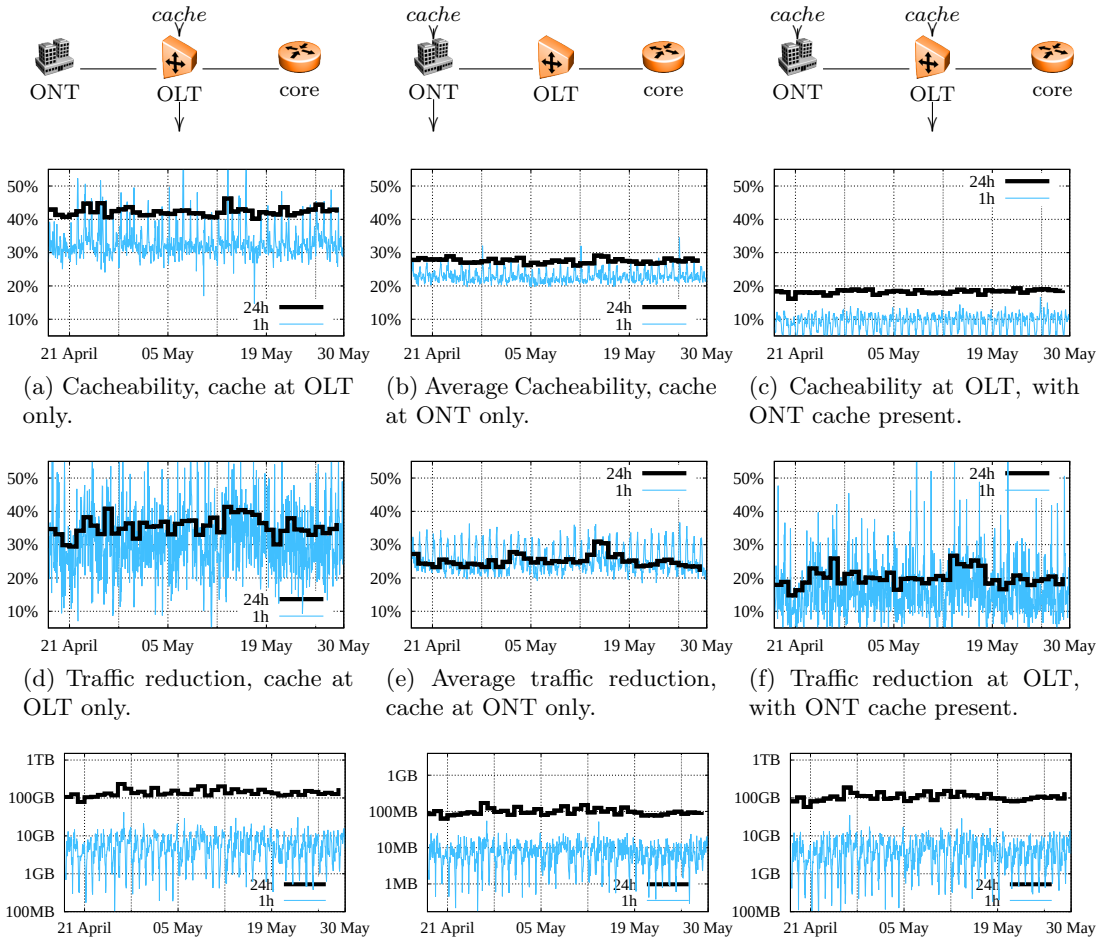
We simulate three different scenarios, in order to asses the impact of a cache in different points of the network.
Cache at vantage point only (OLT). This simulates a transparent proxy, placed as close as possible to the users, but still in the network of the operator. This is a rather simple setup, with only one cache. The challenges here are the speed, since many clients would hit the cache, and the encapsulation, since the packets would still be encapsulated in the access L2 protocol (e.g. PPPoE).
Caches at the users only (ONT). This simulates a transparent proxy installed on the home routers of the clients. This is also a simple setup, although it involves a significant amount of caches. The challenges here are (i) in the sizing of the caches, since some heavy

users won't benefit from the relatively small cache on their router, and (ii) deploying and maintaining thousands to millions of transparent proxies on the routers of the clients. *Caches placed both at the vantage point and at the users (OLT and ONT).* This simulates either a network of transparent proxies, or a deployment of CCN in a real network, where each node in the network is also a cache. In case of transparent proxies, some challenges remain (deployment, encapsulation), while other go away or are less relevant (cache sizing, since there is now a big cache above the clients, and line speed, since now fewer requests make it to the OLT cache). In case of a CCN deployment, there are none of the challenges, because caching is built-in.

4.3.2 Cacheability, Traffic reduction and Virtual cache size

We now analyse cacheability, traffic reduction and virtual cache size, as introduced in Sec. 4.1. We simulate the three scenarios as follows: in the *first scenario* all statistics are simply calculated on the whole dataset; in the *second scenario* all statistics are first calculated per-client, and then the mean average of all clients is then calculated. The clients are identified by MAC address, as already explained in Sec. **??**; in the *third scenario* object cacheability is calculated per-client, like in the previous scenario. Per-client cacheable requests are then filtered out, all the remaining requests are put together, and all the statistics are then calculated on the resulting dataset. This simulates a perfect cache at each client plus a cache at the OLT. The performance of the cache at the clients is not analysed in this scenario because it would obviously be the same as in the previous scenario.

Fig.4.7 plots cacheability (top row), traffic reduction (middle row) and virtual cache size (bottom row), over more than one month in 2014, over hourly and daily timescales. Different scenarios are arranged by columns: namely OLT-only caches (first scenario, left column), ONT-only caches (second scenario, middle column) or OLT+ONT caches (third scenario, right column). The OLT-caching scenario in the left column of Fig.4.7(a),(d),(g) is striking: with a little more than 100GB of memory, 35% of average traffic can be saved for a user fan-out equal to 2048. In the ONT-caching scenario, only duplicated requests coming from the same users are filtered by the cache. In that case, an average memory size of about 100MB per user (thus adding up to 200GB in total, given the user fan-out) reduces user traffic by 25%, corresponding to a same level of load reduction in the GPON access. Finally, the last column of figures, Fig.4.7(c),(f),(i), shows that employing caches at both OLT and ONT level, the ISP network would benefit from 25% load reduction in the GPON and 35% on back-haul links, while improving the latency for all users. We



(a) Cacheability, cache at OLT only.

(b) Average Cacheability, cache at ONT only.

(c) Cacheability at OLT, with ONT cache present.

(d) Traffic reduction, cache at OLT only.

(e) Average traffic reduction, cache at ONT only.

(f) Traffic reduction at OLT, with ONT cache present.

(g) Virtual cache size, cache at OLT only.

(h) Average virtual cache size, cache at ONT only.

(i) Virtual cache size at OLT, with ONT cache present.

Figure 4.7: Time evolution of hourly and daily statistics; by rows cacheability, traffic reduction and virtual cache size are reported respectively in the three cases: (i) cache at OLT only, (ii) cache at ONT only and (iii) cache at OLT and ONT.

can thus conclude:

Observation 4.3.1. *Due to temporal correlation of requests, sizable traffic reduction (in both the GPON and back-haul), can be achieved via deployment of caches of relatively modest size (estimated through the virtual cache size).*

We now briefly compare the statistics above with the ones from the second dataset. The probe is now at the BAS (see Fig.3.1), therefore closer to the core of the network; the user fan-out is significantly higher than in the first dataset (about 30 000 unique users). Our interest in not to repeat the whole analysis, but rather to see whether the

cacheability and traffic reduction are compatible with the results shown above for the first dataset.

The averages of the daily cacheability and traffic reduction metrics, calculated over the whole dataset are respectively 53.6% and 40.2%. Notice that, considering only Web connections (TCP port 80 or 443), 35.5% of the connections and 30.4% of the traffic was SSL: while this represents a noticeable increase compared to the old dataset, it does not invalidate the methods used, because the remaining unencrypted (and therefore analyzable) traffic is still a meaningful share of the total. We thus gather:

Observation 4.3.2. *Cacheability and traffic reduction statistics are in line with those presented in the previous sections, and in particular the difference between cacheability and traffic reduction is preserved. The higher values are a direct consequence of the higher level of aggregation achieved in the new location – which explicitly confirms the conservativeness of the results gathered in the previous sections.*

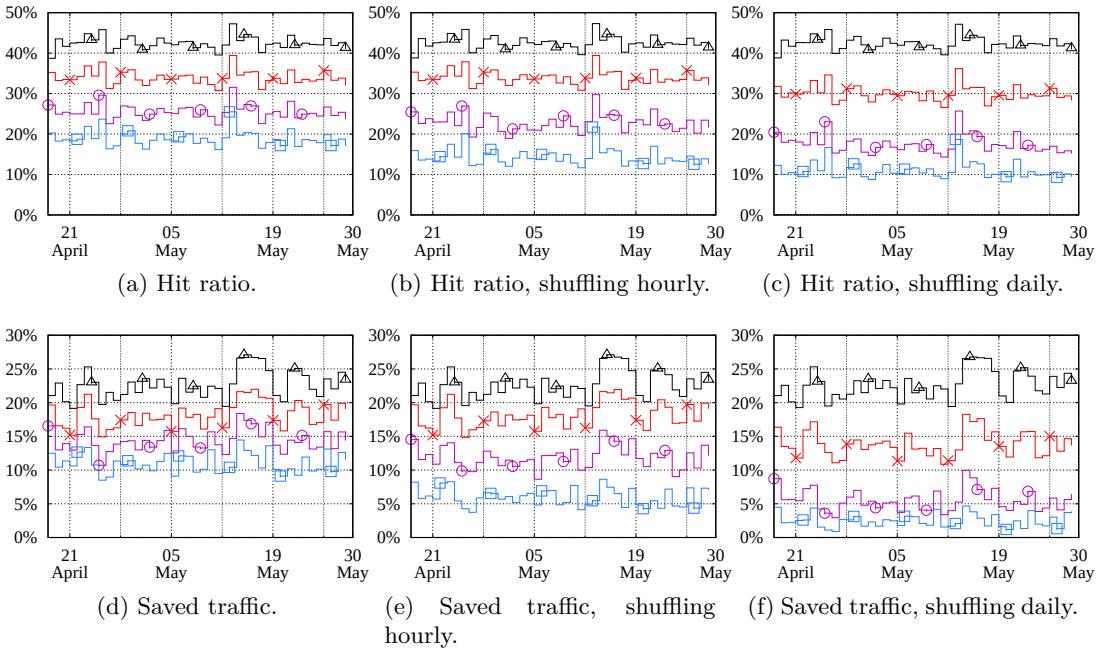
4.3.3 LRU cache simulation

The first set of simulations is based on LRU caches, set up in accordance with the three scenarios, and driven by real users' requests. We simulate LRU caches with different sizes and measure the average hit ratio and the potential traffic savings over a 1 day timescale. The LRU caches simulates a transparent cache: a web object is stored in chunks, so that in case of a cache miss, only the missing chunk is requested. A following request for a bigger part of an object partially present in cache generates another miss, but only for the missing part of the object.

For each scenario, the statistics are calculated from the real traffic, and from two additional artificial request streams generated by uniformly shuffling the real requests in 1 hour and 1 day timeslots. Request shuffling is useful to remove time correlation, which has huge impact on cache performance as already discussed in Sec.4.2: in particular, shuffling produces a workload closer to that of IRM model.

We start by considering cache sizes of 1GB, 10GB, 100GB and 1TB at the OLT (first scenario), and use standard LRU replacement. Its performance is reported in Fig.4.8(a),(d) and compared with the two additional systems obtained by shuffling all the requests on a hourly and daily basis, reported in Fig.4.8(b),(e) and Fig.4.8(c),(f) respectively.

Similar results are shown in Fig.4.9 for the second scenario, where the average and standard deviation for cacheability, traffic reduction and virtual cache size for all clients are shown. In this case the caches have sizes of 10MB, 100MB, 1GB and 10GB. The



(a) Hit ratio. (b) Hit ratio, shuffling hourly. (c) Hit ratio, shuffling daily.

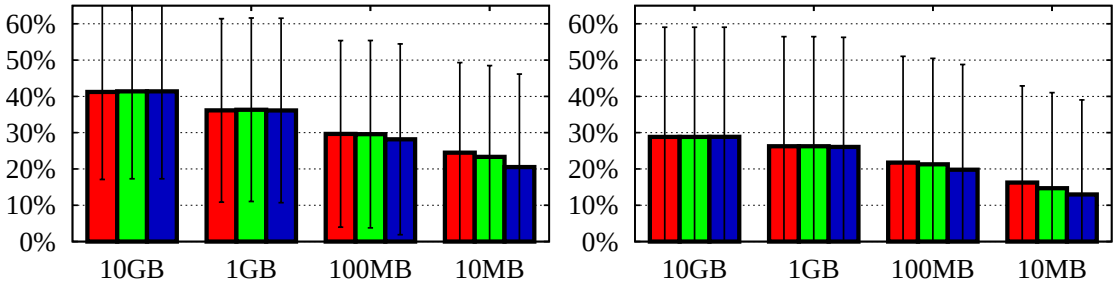
(d) Saved traffic. (e) Saved traffic, shuffling hourly. (f) Saved traffic, shuffling daily.

Figure 4.8: LRU cache simulations, behavior with one-day timeslots. First scenario: cache at OLT only. Cache sizes: △: 1TB, ×: 100GB, ○: 10GB, □: 1GB.

standard deviation shows that the actual behavior of the clients is far from being homogeneous: while some clients exhibit very redundant request patterns (over 60% of cacheable traffic), patterns of others clients are completely uncacheable. Traffic reduction shows an even more drastic variance compared to cacheability.

Finally Fig.4.1 shows the results for the third scenario; since there are now two independent caches with varying size, only a global average is presented. The numbers indicate only the performance of the OLT cache because the ONT caches will behave exactly as in the second scenario; since the OLT cache only processes requests from ONT, the performance of the ONT cache itself is not influenced by the presence of the OLT cache.

From the simulations we see that if the cache is big enough (1TB for the OLT, 10GB for the ONT), time correlations do not have impact on performance. For medium or small caches, instead, the performance in presence of temporal locality of requests is more than halved in the first scenario; in the second scenario the performance is also impacted, but not as badly as in the first scenario. The third scenario, instead, shows some numbers that are at first sight counter-intuitive, but are easily explained considering that the performance of the ONT and OLT caches is inversely related. Whenever the lower level



(a) Hit ratio (b) Saved traffic

Figure 4.9: LRU cache simulations, behavior with one-day timeslots. Second scenario: cache at clients. Average and standard deviation of the hit ratio and saved traffic for all clients, for different ONT cache sizes. Actual traffic:■; 1h shuffled traffic:■; 24h shuffled traffic:■.

caches are too small or ineffective, the upper level will receive more cacheable traffic, and its performance will therefore increase. In particular we observe that both smaller ONT caches and shuffling cause an improvement in the OLT performance. The presence of a relevant amount of cacheable traffic at the OLT even in presence of big ONT caches shows that there is indeed a consistent amount of shared traffic between different clients; even with huge 10GB caches at the ONT, more than 8% of the traffic is still cacheable at the ONT. We can summarize the above with the following observation:

Observation 4.3.3. *A considerable part of the traffic is cacheable; a large part of the overall cacheability is due to repeated requests by the clients, but a considerable fraction of the requests are still shared across different clients. Therefore it makes sense to place caches at both the ONT and OLT. Moreover, due to the large variance in the performance of ONT caches, a cache at the OLT is needed anyway to catch the objects requested by users whose traffic pattern is not cacheable at the ONT. Specifically, ONT cache is beneficial to reduce the load in the access part (which is often a shared medium like Fiber in our case or Cable), while ONT cache is useful to relieve the load in the upstream backhaul network (which is a precious resource as well).*

4.4 Object identification

Cacheability and traffic reduction both heavily depend on a correct identification of the transferred objects in order to determine if a given object was requested more than once. This section thus aims to explain the systems used to identify and distinguish the objects. Especially, our aim is to assess the robustness of the previous findings against

	1GB	10GB	100GB	1TB
10MB	3.2	8.9	18.2	28.7
100MB	2.2	6.7	15.2	25.6
1GB	1.6	4.8	11.8	20.7
10GB	1.5	3.6	9.2	16.6

(a) Hit ratio (%).

	1GB	10GB	100GB	1TB
10MB	2.5	9.1	20.2	30.5
100MB	1.5	6.2	15.7	26.0
1GB	0.9	4.2	11.7	20.7
10GB	0.7	3.1	9.1	16.5

(b) Hit ratio (%), shuffling hourly.

	1GB	10GB	100GB	1TB
10MB	2.4	7.4	19.3	33.4
100MB	1.2	5.1	14.5	28.2
1GB	0.5	3.0	10.2	21.1
10GB	0.3	1.8	7.6	16.4

(c) Hit ratio (%), shuffling daily.

	1GB	10GB	100GB	1TB
10MB	4.3	7.4	11.3	16.1
100MB	2.0	4.1	7.9	12.8
1GB	1.6	3.1	6.3	10.7
10GB	1.6	2.7	4.8	8.1

(d) Saved traffic (%).

	1GB	10GB	100GB	1TB
10MB	2.0	7.6	13.6	18.3
100MB	0.6	3.8	9.2	14.0
1GB	0.4	2.4	6.5	10.9
10GB	0.4	2.0	4.9	8.2

(e) Saved traffic (%), shuffling hourly.

	1GB	10GB	100GB	1TB
10MB	0.6	3.0	10.9	20.0
100MB	0.2	1.5	7.1	16.4
1GB	0.2	1.1	4.4	11.7
10GB	0.1	0.9	3.4	8.2

(f) Saved traffic (%), shuffling daily.

Table 4.1: LRU cache simulations, third scenario: cache system with cache at clients and at vantage point; averages of daily values. The behavior of the ONT caches in the third scenario is exactly the same as in the second scenario. Client caches of sizes 10MB to 10GB; vantage point cache sizes of 1GB to 1TB.

different, increasingly sophisticated, object identification methods. This is important not only from a methodological point of view, but also because, to our knowledge, this kind of analysis is novel.

Before introducing the technique we consider, we need to introduce protocol details to illustrate the design space for object identification.

4.4.1 HTTP Transactions and Headers

An HTTP transaction consists of a request from a client and its reply from the server. The request consists of a method (usually GET), a resource, and the HTTP version supported by the client, followed by some headers. The reply consists of the HTTP version supported by the server, a numerical code indicating the outcome of the request, and an optional description, followed by some headers. All headers have the same structure: they are simple key-value associations. Each HTTP transaction has several headers and properties that can be used to identify objects, the most obvious one is the resource part of the request, which, together with the `Host` header constitutes the URL.

A useful, optional, information is carried by the `ETAG` header. ETAG consists of a string that uniquely identifies the specific version of the requested content so that, when present, it gives a clear indication if two transactions for the same URL are about the

same underlying object. ETAG is generally used for caching purposes: the client can perform ETAG-based conditional GETs, and the HTTP standard mandates that the same URL with the same ETAG should correspond to the same content. Using the ETAG therefore allows to distinguish between different versions of the same page (e.g. news websites). Table 4.2 shows that more than 30% of the observed requests have an ETAG header.

Table 4.2: Statistics of headers useful for content identification (top) and comparison of the first two identification methods (bottom)

HTTP requests	Occurrence	Penetration
with ETAG	116 819 069	31.64%
with cookies	191 075 062	51.75%
`Range` requests	6 869 802	1.86%

Identification method	Distinct objects
URL+ETAG	174 283 000
URL+ETAG+size	184 122 000

HTTP range requests. instead, complicate the matters. A client can request only a given byte range of the content, using the `Range` header, and if the server supports range requests, a `206 Partial Content` reply is issued instead of the usual `200 OK`, the `Content-Length` header indicates at this point the length of the requested range. An additional `Content-Range` header is also issued in the reply, indicating the byte range and the total length of the object. If the server does not support range requests, it will reply with the whole object, disregarding the `Range` header. Range requests are used mostly in three cases: to transfer large amounts of data in a safe and verifiable way, to perform media streaming, and to resume interrupted downloads. The first case relates to big downloads, mostly performed through specialized clients, like system updates, where the client can verify and re-request corrupted pieces of the file, without having to download all of it again. The second case is for media streaming (audio and/or video): the client requests pieces of the media as the media itself is being played to the user, and as users might skip to random parts of the video, they could thus not be downloading the whole object. The third case is the simple case where a download was interrupted for any reason (e.g. poor Wi-Fi coverage, software crash, battery discharged, etc), and then resumed. In most (but not all) cases the client will only attempt to download the missing parts. We observed all of the above behaviors in our dataset; moreover the average size of all HTTP transactions observed in our dataset is 110KB, whereas the average size

of transactions with range requests is 1161KB, which is over 10x times bigger and is in line with the explanations above. Therefore, despite being less than 2% of the requests, range requests can potentially represent 20% of the traffic, thus our interest in assessing their real impact.

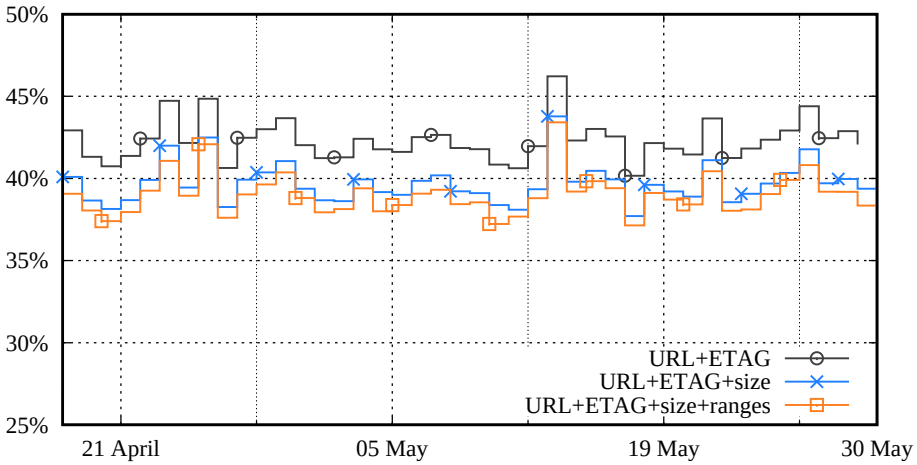
There are several other headers that can potentially influence the content returned by the server for the same URL – including cookies, language, user-agent and referrer headers. At each transaction, servers may request cookies to be stored by the client (`Set-Cookie` header), which the client will subsequently send back to the server (`Cookie` header) when requesting further objects. Cookies are ubiquitously used for tracking users and potentially serve personalized content – yet different cookies do not automatically imply different content. Clients can specify a list of languages they like (`Accept-Language` header), and the server can specify which language is being used in the reply (`Content-Language`). This is used to get the content in a language the user understands, since many popular websites offer their content (or at least their interfaces) in different languages. Almost all clients send the `User-Agent` string, which should serve to identify the client software (and its version) for statistical purposes. Yet this is also being increasingly used to serve different versions of the content depending on the browser vendor, to work around specific bugs or take advantage of specific features, or to serve a mobile version of the page in case a mobile browser is identified. Finally, most clients send the `Referer` header, i.e., the URL of the previous web page from which a link to the currently requested object was followed: content can differ for different referrers. Given that none of these headers deterministically imply different content, their usage is non trivial, and we disregard them in the following.

4.4.2 Object identification strategies

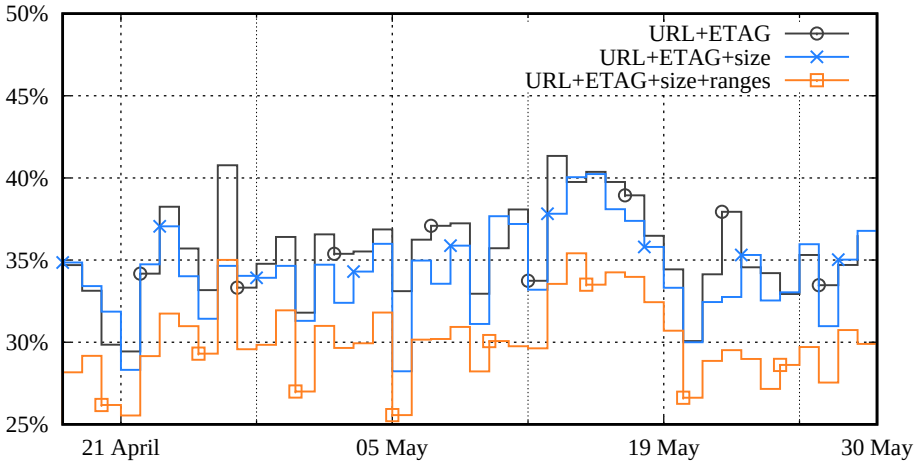
Object identification strategies leverage protocol information described in the previous section. Since many designs are possible, we select three representative strategies, that span the whole spectrum in terms of implementation complexity:

1. A simple strategy that only considers the URL and the ETAG.
2. A slightly more complex strategy that combines the ID from the previous point with the sizes of the objects.
3. A considerably more complex strategy that combines the ID from the previous strategy with an accurate tracking of the requested ranges.

The first two methods are rather simple and fast to compute (per-flow log, processing in the order of minutes for our datasets) whereas the third method comports a consid-



(a) Cacheability, cache at OLT only.



(b) Traffic reduction, cache at OLT only.

Figure 4.10: Time evolution of daily statistics. Comparison of cacheability and traffic reduction calculated using three increasingly complex methods.

erable usage of resources (per-range request log, processing in the order of hours). The first strategy is obviously the easiest to implement, as only the URL and (if present) ETAG are needed. The simple model behind it is a "normal" cache that will fetch the whole object as soon as any part of it is requested.

The second strategy also considers the size of the objects. The total size of the object is extracted, in order of preference, from the `Content-Range` header, from the `Content-Length` header or finally from the real number of bytes transferred. This allows to distinguish with more accuracy when the same URL yields different objects, as their

size will likely be different, making therefore unnecessary to track the other HTTP headers described in the previous section. Effects of range requests are still ignored.

Finally, the third strategy adds a complete state tracking of all the requested ranges. In this scenario a request is considered cacheable only if it overlaps at least partially with a previous request. Only the range of effectively transferred bytes is counted, so a resumed interrupted download is not considered as a hit, provided there was no overlapping with any other previous request for that object. Objects themselves are identified with the same system as the second strategy. This strategy considers an object cacheable w.r.t. traffic reduction if at least one of the partial requests was a hit.

Fig. 4.10 shows the comparison of the cacheability and traffic reduction using the three systems, on 1-day timeslots. It can be seen that there is very little difference between the first two methods, and the third method is also not too distant. The reason for the lower value of the traffic reduction for the third method is that, in case of transactions that are fragmented in multiple range requests, most of the fragments are big (because of the type of objects that are usually fetched with range requests, as previously explained), and most of those requests are cache misses. With the first two methods those requests are considered as hits, because they all involve the same object, and therefore all the traffic they generate is considered cacheable whereas with the third method, requests for non overlapping ranges are considered non cacheable. Fig.4.11 shows the distribution of the real size of the objects transferred with and without range requests. It can be observed that not only the single transactions, but also the objects themselves that are transferred using range requests are larger than the ones that are transferred without range requests.

Observation 4.4.1. *Accurate object identification would benefit from a significant level of protocol details to be taken into account. Simpler object identification techniques, such as the URL+ETAG method lead to slight overestimation of traffic cacheability and reduction, but are comparatively extremely simpler to implement and thus justifiable as a good compromise for large-scale online traffic analysis.*

4.5 Discussion

The significant potential gains we have measured in today traffic does no apply to encrypted web applications (15% in the first dataset, 30% in the second, steadily increasing) which cannot be transparently cached. Caching TLS encrypted traffic is however going to be a significant issue for ISPs as it would require some form of interaction with

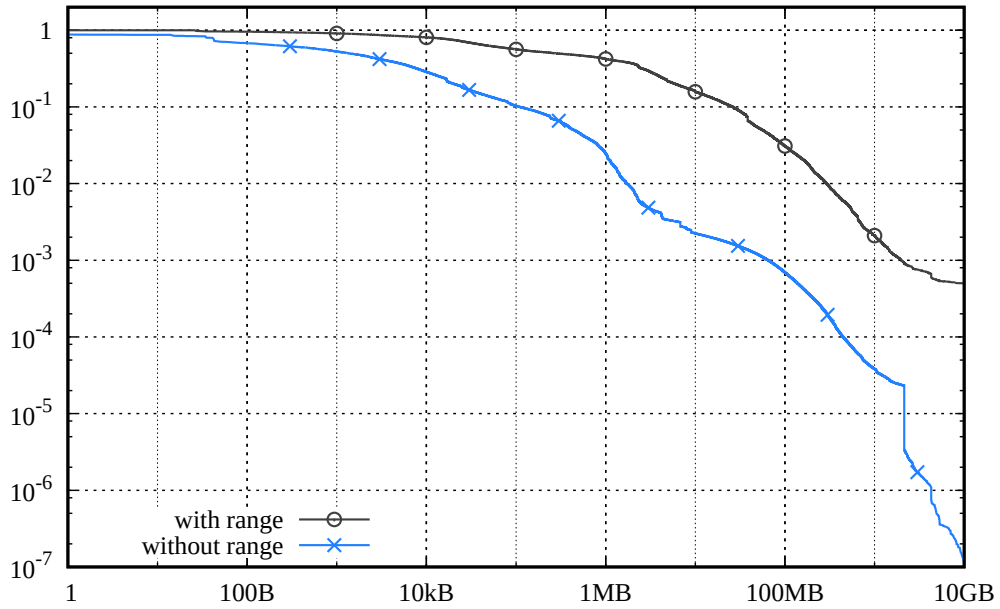


Figure 4.11: Distribution of the sizes of the objects requested with or without range requests. Reverse CDF.

the content provider, or the CDN on its behalf. Transparent caching of encrypted traffic might also be achieved by TLS tunnels interception which implies some form of increased vulnerability at the user's client. We suggest instead to use CCN as the best fit technology to address all the drawbacks of currently available workarounds and providing caching as a transparent network primitive. We additionally assess technical feasibility in nowadays hardware, and argue that such a small amount of additional memory can be supported at high speed on current technologies. We finally identify steps for micro-CDN implementation, outlining arguments to support a CCN-based deployment as basic building block. Our analysis suggests that CCN-based solutions are close enough to be deployed in real ISP networks – its realization is part of our ongoing work.

4.5.1 Technical feasibility

Previous sections have shown that significant benefits in terms of traffic reduction can be achieved at the cost of very limited additional memory. Indeed, a single ONT installed in a user's home would only need approximately 100MB of additional memory. Such memory, currently not available in optical devices, is available in the home gateways, that are equipped with enough CPU resources to easily manage 100MB of RAM at 1Gbps. Upstream to the OLT, 100GB memory in a router line card would be enough to

provide the early shown gains and it seems feasible in current hardware [73]. Hence, the deployment of a micro CDN technology in the home would only require to implement the content-centric forwarding engine in the home gateway firmware – which again seems feasible due to the current development effort on several CCN/NDN prototypes.

4.6 Summary

In this thesis we provide evidence of the potential gains associated to the deployment of micro CDN technologies in ISP networks. Our analysis is grounded on a large dataset collected via the on-line monitoring of links between the access and the back-haul network of Orange France. Leveraging several months of continuous traffic monitoring in different vantage points in the operational network, we are able to support our design by an accurate characterization of content dynamics.

The large data set we have used allowed fine-grained statistical analysis of content popularity dynamics, whose value goes beyond the primal objective of this thesis. Indeed, the analysis demonstrates the inadequacy of traditional models, like simplistic Zipfs workloads, and their failure for prediction and dimensioning. The gains are striking: with a negligible amount of memory of 100MB on CPEs, the load in the access network (GPON) can be reduced by 25%, while embedding a 100GB of dynamic memory in edge IP router line cards can also reduce back-haul links load of about 35%.

Chapter 5

Big Data approach to cacheability analysis

As shown in Chapter 3, we had to handle pretty big datasets; the third dataset, in particular, proved to be impossible to handle on our server, therefore we decided to use a Hadoop cluster to perform the computations. Having so much computing power enabled us to perform more accurate types of analysis, in particular regarding object identification.

This chapter will initially present an improved method to more accurately identify objects, in particular in presence of partial requests. A parallel approach to statistics computations is then presented, including a performance comparison with classical sequential implementations. Finally the results of the computation are presented for the largest datasets, including a performance analysis of different optimizations.

The statistics considered are Cacheability ($1 - \frac{N_o}{N_r}$), Traffic Reduction ($1 - \frac{R_u}{R}$), and Virtual Cache Size ($\sum_{o \in cacheable} V_o$), as introduced in 4.1.

5.1 Analytics

At a finer grain, several implementations of the cacheability, traffic reduction and virtual cache size analytics are possible: ultimately, all these indexes depend on the way in which objects are identified, and the way in which their volume is computed.

5.1.1 Object identification

HTTP object identification can leverage different information such as e.g. object ID, range information, ETAGs, cookies, etc. The *object ID* is a 64-bit value calculated as the

FNV1a hash of the URL of the object concatenated to its ETAG (if present). Similarly, volume estimation can leverage information such as advertised size (HTTP header information), or take into account effective size (HTTP payload actually transferred over the TCP connection). For instance, the effective size is less than the advertised one if the download is interrupted, while in case of range requests, the advertised size is the size of the part of the object that is returned, and not the full size of the object, which is then reported in the range information.

Object identification and size estimation strategies leverage protocol information described above. Since many designs are possible, we select three representative strategies, that span the whole spectrum in terms of implementation complexity:

— *ObjectID:* A simple strategy that only considers the Object ID (URL and the ETAG).

— *Size:* A slightly more complex strategy that combines the ID from the previous point with the full sizes of the objects (advertised size or full object size in case of range requests).

— *Ranges:* A considerably more complex strategy that combines the ID from the previous strategy with an accurate tracking of the requested ranges.

Accuracy vs Complexity Tradeoff

Roughly speaking, we face the following tradeoffs: the *first two methods may lead to overestimation of caching benefits, but they are rather simple and fast to compute.* These methods performs only per-request operations, require only a small amount of memory, are easy to implement using standard UNIX command-line tools and their processing time is in the order of minutes for the typical day in our dataset. The *third method is instead more accurate, at the price of a considerable usage of resources.* The latter method indeed performs per-range request operations, which both increase the required amount of memory as well as the processing time, and is not trivially implemented using only UNIX command line tools. We summarize the properties of these strategies in Tab.5.1, which reports rough projection of time and memory complexity based on our experience on smaller datasets[4]. For the sake of illustration, Fig.5.1 additionally quantifies cacheability and traffic reduction statistics computed from our previous small-scale dataset[4] with classical sequential algorithms.

More in detail, the first strategy is obviously the easiest to implement, as only the URL and (if present) ETAG are needed. The log from the probe already contains this information in usable form (Object ID), so no additional processing is needed. However

Table 5.1: Comparison of the expected performance of the different object identification methods for our dataset

Method (Sec.5.1.1 and 5.2)	**Accuracy** (Fig.5.1)		**Complexity** (Sec.5.3)	
	Object-wise	**Byte-wise**	**CPU Time**	**Memory**
ObjectID	Fair	Fair	Minutes	Few GB
Size	Good	Fair	Minutes	Few GB
Ranges	Very good	Very good	Hours	Hundreds of GB

this possibly overestimates caching gains, which is not desirable.

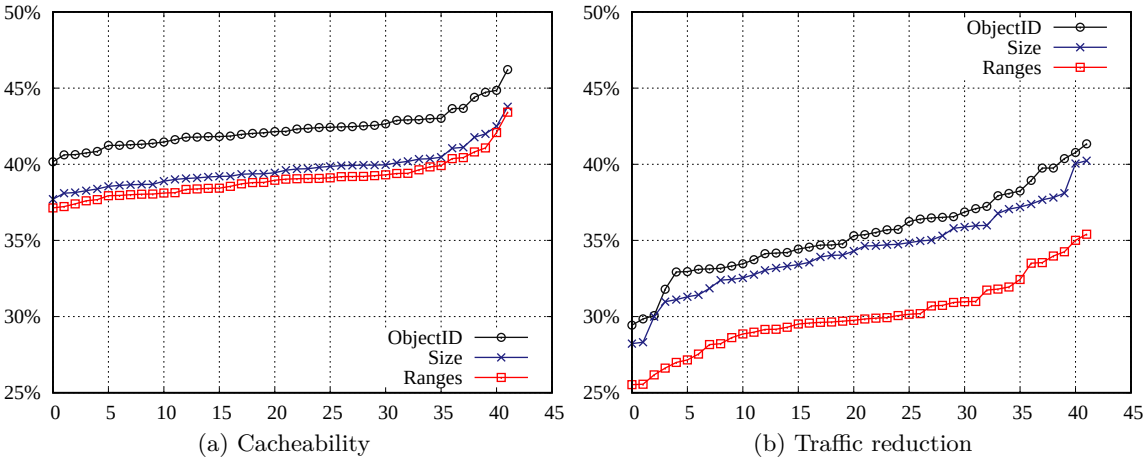
The second strategy also considers the size of the objects. The total size of the object is extracted, in order of preference, from the `Content-Range` header, from the `Content-Length` header or finally from the real number of bytes transferred. This allows to distinguish with more accuracy when the same URL yields different objects, as their size will likely be different, however effects of range requests are still ignored.

Finally, the third strategy adds a complete state tracking of all the requested ranges. In this scenario objects are identified as in the previous strategy, however a request is considered cacheable only if it overlaps at least partially with a previous request. Only the range of effectively transferred bytes is counted, so a resumed interrupted download is not considered as a hit, provided there was no overlapping with any other previous request for that object. This strategy considers an object cacheable w.r.t. traffic reduction if at least one of the partial requests was a hit.

Observation 5.1.1. *In terms of accuracy, the left hand size of Fig.5.1 clearly shows that ObjectID is excessively simplistic in estimating object-level cacheability, whereas Size and Ranges provide very close results. At the same time, the right hand size of Fig.5.1 shows that both ObjectID and Size are excessively optimistic in estimating byte-level traffic reduction, unlike Ranges. It follows that this latter strategy is the most useful for our purposes.*

Implementation considerations

Some additional implementation details are worth highlighting, even in the relatively simple sequential case. Notice that instead of using a comfortable scripting environment, to optimize for speed and memory complexity we opted for a lower-level implementation in C. It follows that our sequential implementation is not very flexible, but instead highly optimized.



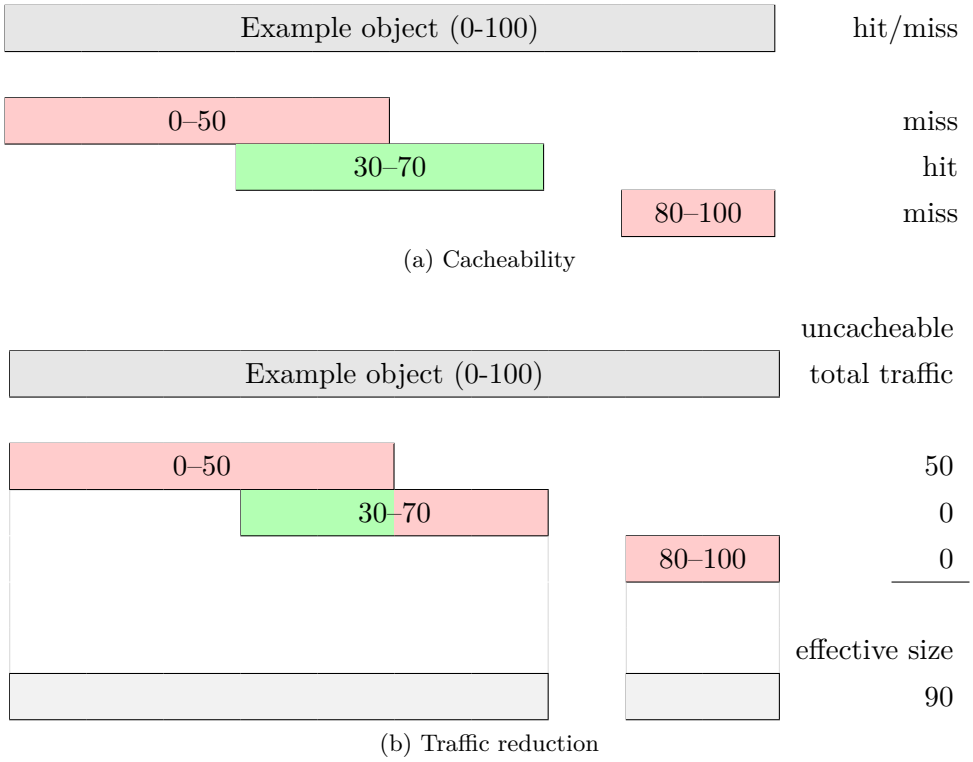
(a) Cacheability (b) Traffic reduction

Figure 5.1: Comparison of the accuracy of the different object identification methods for the [4] dataset. The Y axis reports cacheability and traffic reduction analytics, computed over daily intervals, which are then ranked from lowest to highest gain on the x-axis.

Complexity of the first two strategies (i.e. *ObjectID* vs *Size*) is basically the same. These strategies differ slightly in the way objects are identified: both methods keep the *object ID* and the *effective size* of the object (as the maximum observed value for that object); the second method additionally considers the *advertised size* to further distinguish between distinct objects with the same ID (but different advertised size).

A running sum is kept for the three analytics of interest. For cacheability, it is required to just keep track of the *number of total requests* N_r and the number of *unique objects* N_o: the former is updated at any new requests (i.e. HTTP GET), whereas the second is simply incremented whenever a new object is added to the hashtable. Estimating traffic reduction requires to keep track of *the total traffic generated* R and the *amount of cacheable traffic* R_c: the former is update at any new requests, whereas the cacheable traffic is computed as the sum of all traffic generated by objects seen more than once, whose count is tracked in the hashtable (and updated at each requests provided that the count equals or exceeds 2). For virtual cache size, we keep a running sum of the *effective size* V_o of the objects that are seen more than once, but obviously only once per object: also this last statistic uses the object request count tracked in the hashtable (but is updated only when the count equals 2).

As for *Size*, objects are identified with object ID and advertised size, and the effective size is calculated as the number of unique bytes seen. Similarly to the previous cases, analytics are tracked with running sums. For cacheability, we keep a running sum of the



(a) Cacheability

(b) Traffic reduction

Figure 5.2: Example of hit and miss in presence of range requests and partial downloads. Cache hits are highlighted in green, misses are highlighted in red. Since there is a hit and given how traffic reduction is calculated, all the traffic generated by the object is considered cacheable.

hits and the total number of requests. For traffic reduction, we keep a running sum of the effective traffic for cacheable objects (that is, objects that have at least 1 hit). For the virtual cache size, we keep a running sum of the effective size of all the cacheable objects.

Ranges is more complex: for each object, it needs to keep track not only of its ID, its advertised size and effective size, but also of the *number of hits*, and especially *the list of requested ranges*. The number of hits is necessary because, accounting for range requests, it is possible to see an object request more than once without having a hit, e.g. in case non-overlapping parts of the object are requested, like for chunked or resumed downloads. A request is only considered a miss if no bytes of the requested range of the requested object were requested previously, otherwise it is considered a hit. Partial downloads are also considered as ranges for the observed intervals, and partial downloads of range requests are also properly accounted for.

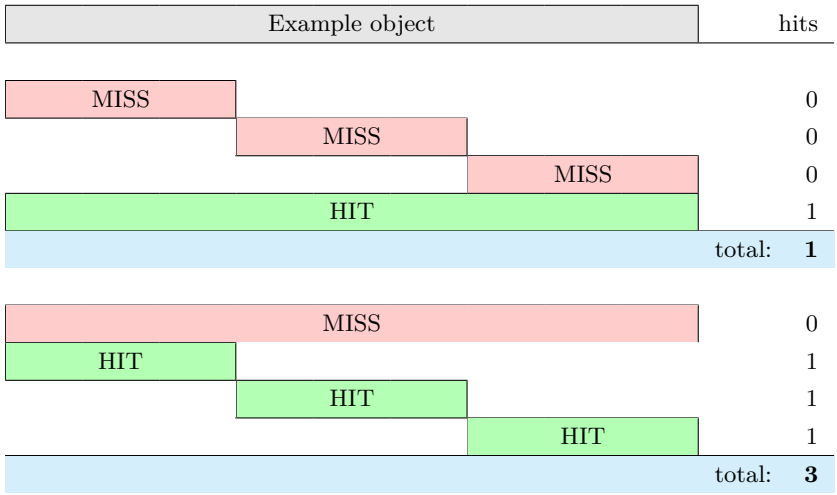


Figure 5.3: Visualization of the importance of the arrival order for counting hits when considering partial requests.

Notice further that the order in which requests arrive is important: for example, an object that is first requested in two chunks and then is requested again entirely will generate only one hit, while the same requests in a different order will generate two hits. This is illustrated in Fig. 5.2 and Fig. 5.3, which show an example of possible criteria for considering a request as a hit or as a miss.

However, differently from the previous cases, range requests make the associate state more complex, and object tracking more involved. More precisely, as shown in Fig.5.2a, any request that overlaps even partially with any previous requests is considered a hit. Counting the number of hits therefore involves *comparing each partial request with all the previous ones* to check if there is an overlap.

Interval merging, is instead needed to properly calculate the virtual cache size. Interval merging is shown in Fig.5.2b, and it is actually performed step by step as new requests arrive, rather than at the end. The merged intervals are also used to check and count the hits, as discussed previously. Keeping only the merged intervals saves time during the computations, since each new interval has to be checked against a smaller number of other intervals.

5.1.2 Input dataset

While it is outside of the scope of this thesis to describe HACkSAw[74], the software tool that we deployed in a passive probe in the operational network of Orange, we however need to briefly comment on some details of the dataset. While we de-

ployed HACkSAw in different levels of aggregation, in this work we focus on monitoring 2x10Gbps links at a PoP serving a population of about 40,000 users. The software outputs a plaintext database, with about 25 columns per file, and one file for (i) TCP flows, (ii) UDP flows, (iii) HTTP transactions, (iv) DNS requests. Nearly 200,000,000 rows per day are generated, which amounts to about 100GB daily.

Statistics about the total and daily volumes are tabulated in Tab.3.2, which also reports a comparison with datasets used in our previous work [4] and in related work. It can be seen that the dataset we considered here has the *longest duration* (3× our previous work and over 10× longer than in the related literature), has the *largest number of requests* (70× our previous work and over 4× the largest dataset in related literature), the *largest number of objects* (50× our previous work and about 3× the largest dataset in related literature), that correspond to the *largest traffic volume* (100× our previous work and about 10× the largest dataset in related literature).

The sheer dataset size poses significant computational challenges, even for our highly optimized ANSI C implementation: it can be seen that the big dataset has more than $8{\cdot}10^9$ distinct objects, with a daily average of $90{\cdot}10^6$. Grouping by sorting is prohibitively time consuming, and needs too much temporary storage. We also project that computing the previously illustrated analytics grouping by day using a hashtable is also prohibitive. We lower bound the memory size of such an hashtable by considering that, at a minimum for each object we need at least to keep track of (i) object ID, (ii) advertised size, (iii) effective size, (iv) timestamp, and (v) number of hits. Additionally, each object needs (vi) a pointer to the next object in the hashtable, (vii) a pointer to the list of chunks, and (viii) at least one chunk with pointer to next, (iv) a start and (x) end offsets. Each of those items takes up 8 bytes for a total of at least 80 bytes per object. Considering the rate of distinct objects per day $\Lambda = 9 \cdot 10^7$ objects/day, the size $S = 80$ bytes/object of each object, and the length $t = 132$ days of out dataset, we need $S\Lambda t = 80{\cdot}(9{\cdot}10^7){\cdot}132 \approx$ 950GB of memory, just to compute the three key statistics mentioned above, across the overall dataset. This is of course a very optimistic lower bound since we are overlooking the fact that some objects will have more than one chunk. On top of that, we are also ignoring all the other data structures used to implement the hashtable.

Of course, according to the above projections we estimate that our ANSI C implementation should still be capable to compute daily statistics on the new dataset (where some 10GB of RAM should suffice). At the same time, it also appears that big-data approaches such as Hadoop seem an interesting option to scale the analysis of the current dataset, with the added benefit of gaining horizontal scalability to further scale this up analysis in time (e.g., extended durations), space (e.g., considering multiple probes, or

```
A0 = LOAD '$inputfiles' using PigStorage('\t') AS (f1:chararray, f2:chararray,
 f3:chararray, f4:chararray,f5:chararray, f6:chararray, f7:chararray, f8:chararray,
 f9:chararray, f10:long,f11:chararray, f12:chararray, f13:chararray, f14:chararray,
 f15:chararray, f16:chararray, f17:chararray, f18:long);

in = FOREACH A0 GENERATE f12 AS ID, f18 AS Traffic,
 (f10/(3600L*1000000L)+2L)/24L AS TimeStamp;

o = foreach (group in by (ID,TimeStamp)) generate FLATTEN(group) as (id,ts),
    (long)COUNT(in) as nreq:long, (long)SUM(in.Traffic) as tr:long,
    (long)MAX(in.Traffic) as size:long;

ct = foreach (group o by ts) {
 ids = o.id;
 objects = DISTINCT ids;
 cac = filter o by (long)nreq>1L;
 generate (long)(group*24L-2L)*3600L as ts:long, (long)COUNT(objects) as no:long,
  (long)SUM(o.nreq) as nreq:long, (long)SUM(o.tr) as tr:long,
  SUM(cac.tr) as cact:long, SUM(cac.size) as vc:long;
}

STORE ct INTO '/User/pigoutput' using PigStorage(' ');
```

Figure 5.4: PIG code of ObjectID. While not particularly elegant, the code is however very compact with respect to the about 1,200 lines of code our ANSI C implementation.

a larger user-base) or line-rate (e.g., moving the probe to a higher level of aggregation),

5.2 Parallelizing caching analytics

We parallelize the analysis of caching analytics by leveraging a big-data cluster in Orange. While for reason of confidentiality we cannot fully disclose details of the cluster, for the purpose of this work it is largely sufficient to say that the cluster is based on Apache Hadoop and it has over 2,000 cores.

The workflow has been automated to gather up-to-date statistics without requiring human intervention. A script is run periodically on the probe to compress the logs of the previous hours, which are then transferred to a gateway that will decompress and inject the data in the Hadoop cluster. The compression is needed to minimize the bandwidth requirement between the probe and the cluster, which are in different networks.

Oozie is used both to automate and coordinate the compute jobs. The Oozie job serializes the first and second map-reduce jobs, starting the second one only if the first

one was successful. The Oozie job runs the task on the cluster at regular intervals (namely: hourly and daily) and the results are then copied to a web server for display.

In the reminder of this work, we limit ourselves to analyze and benchmark the analytics, and disregard all aspects such as automation that, albeit extremely important from an operational viewpoint, are however less relevant from a scientific standpoint.

5.2.1 Design choices

There are several approaches that can be used to process large amounts of data. Traditional SQL databases, for example, are very well suited to process large amounts of data. We however need not only to analyze a sheer amount of data, but also to perform fairly complex calculations on the data (e.g. range reconstruction/consolidation). At the same time, while traditional SQL databases are not suitable for our purposes, there exists SQL-like interfaces built on top of the Hadoop framework, such as PIG or Hive, that are thus worth considering.

For illustrational purposes, Fig.5.4 shows the PIG code of ObjectID strategy for object identification. Gains are clear by considering that o our ANSI C implementation amounts to over 1,200 lines of code, which is in part due to the lack of even basic structures such as hashtables in ANSI C.

However, simplicity is not without cost. Indeed, PIG hides the complexity of a native implementation in Map-Reduce, but at the same time does not allow to optimize the usage of Map-Reduce jobs as a native Java implementation would allow. In the rest of this section, we describe our native Java implementations of the early illustrated cacheability analytics.

5.2.2 Map-reduce analytics

We implement the cacheability, traffic reduction and virtual cache size analytics with a *two-stages* Map-Reduce configuration. Irrespectively of the specific object identification method, the general architecture of the map-reduce jobs is similar, and schematically illustrated in Fig.5.5.

The two stages differ slightly depending on the object identification method. In the *ObjectID* and *Size* cases, the *first map* parses the input lines and groups the requests by timeslot and ID (or extended ID, that is the object ID together with the advertised object size,in the *Size* case). The *first reduce* computes the aggregate per-object/per-timeslot values. The *second map* is just the identity function, while the *second reduce* step aggregates all the values for all the objects in each timeslot.

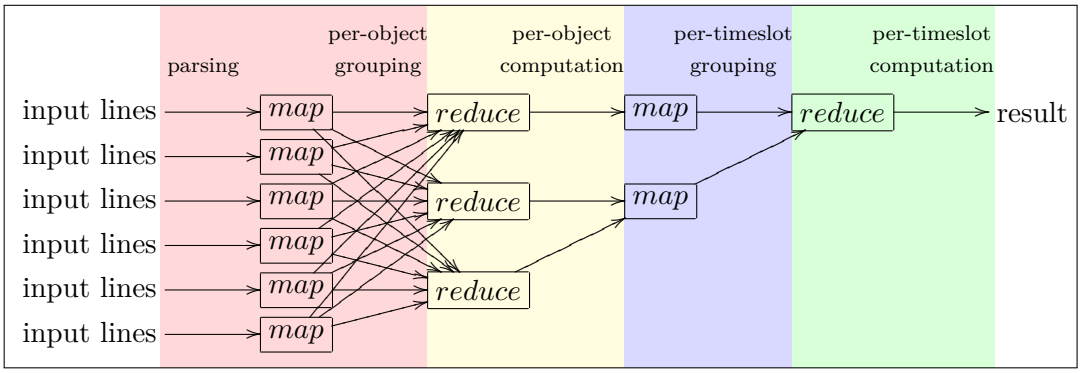


Figure 5.5: Dataflow in the two-stage Map-Reduce. Colors highlight the various stages.

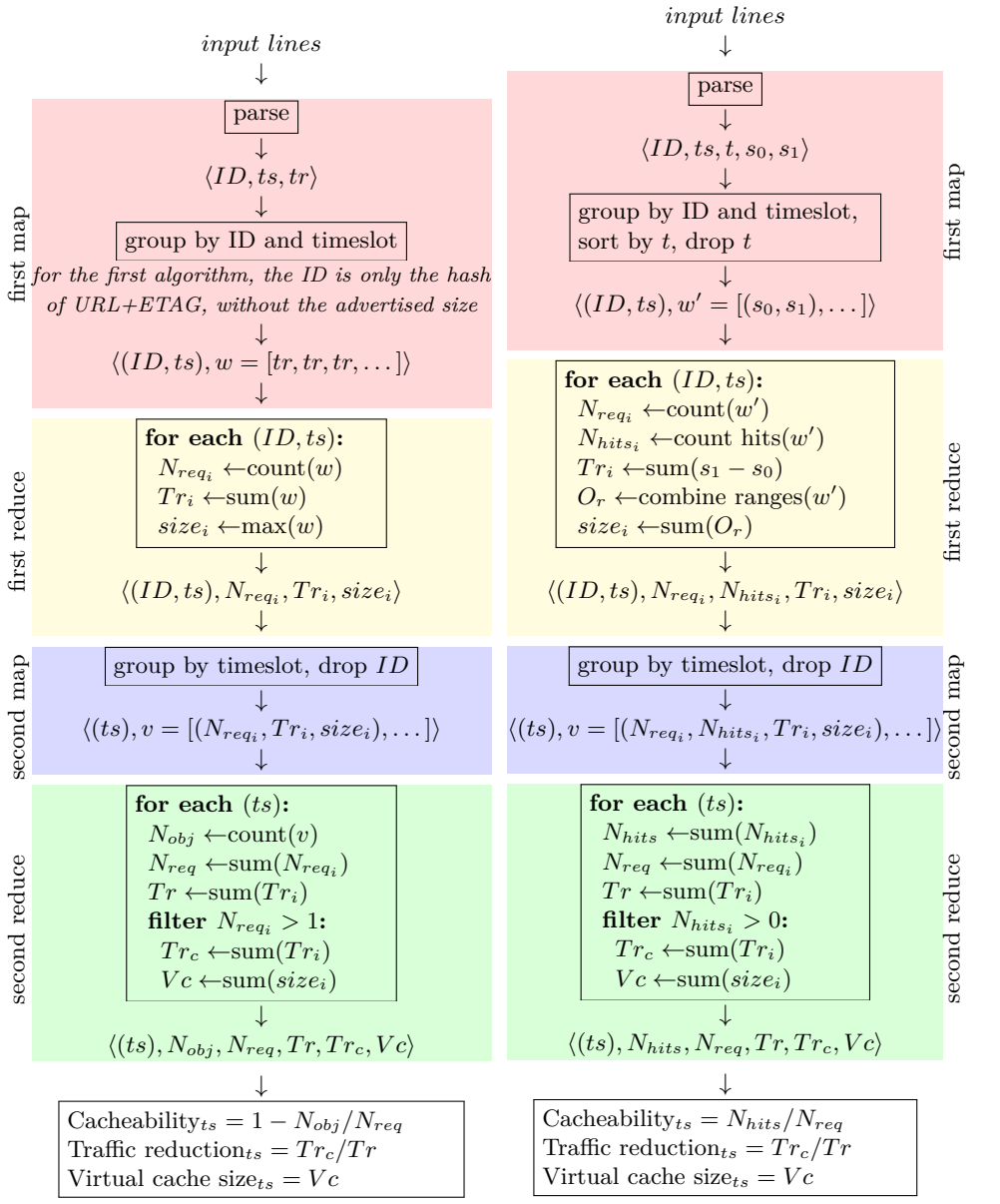
In the *Ranges* case, the order of arrival is especially relevant for accuracy, so that this algorithm needs to sort request by time inside each timeslot after the first map. Then, the first reduce step merges all requests for different chunks of the same object, properly calculating the number of hits and the amount of generated traffic. After the first reduce, for each object, we have the number of requests, number of hits, total traffic and number of unique bytes.

Analytics are presented in more details in Fig. 5.6, which graphically shows the dataflow in greater detail and the actions performed in each phase. The first step, common to all algorithm is input parsing. Text input lines are parsed, invalid lines are discarded; the number and type of fields parsed is instead algorithm dependent. Invalid lines can arise from bugs in the capture tool, data corruption on the path to the Hadoop storage or finally corruption in the Hadoop storage itself. We now comment each of theses phases, for all algorithms, in more depth.

ObjectID and Size analytics

Analytics based on *ObjectID* or *Size* object identification strategies are represented in the left hand side of Fig. 5.6. For each request, the first two algorithms (*ObjectID*, *Size*) parse the ID, the timeslot and the amount of traffic generated for that request. The ID is only the Object ID for the *ObjectID* algorithm and is the concatenation of Object ID and advertised size for the *Size* algorithm.

The requests are then grouped by ID and timeslot. Each slot will therefore contain all the requests for a specific object in a specific timestamp, with ID and timeslot as key, and the list of generated traffic as value. For each slot three statistics are calculated: the number of requests for that object in that timeslot, which is simply the length of the



(a) ObjectID and Size

(b) Ranges

ID: Object ID+advert.size	N_{obj}: Number of objects	N_{hits}: Number of cache hits
ts: Timeslot	N_{req}: Number of requests	t: Timestamp (μs)
tr: Traffic	Tr_c: Cacheable traffic	s_0: Start of range
$size$: Effective size	Vc: Virtual cache size	s_1: End of range
		O_r: Object ranges

Figure 5.6: The three algorithms. The same colors as in Fig.5.5 are used to help identify the map-reduce stages.

list; the total traffic generated by that object, calculated as the sum of the list; and the effective size of the object, calculated as the maximum value in the list.

The elements are now grouped by timeslot only: the timeslot is thus the key and the value is a list of tuples, one for each object in the timeslot, with the values calculated in the previous step. The final statistics are now calculated. The number of distinct objects is calculated simply as the length of the list. The total number of requests is calculated as the sum of the requests for each object; the total traffic is calculated as the sum of the traffic generated by each object, the cacheable traffic is calculated as the sum of the traffic generated by the objects that were requested more than once; the virtual cache size is calculated as the sum of the effective size of the objects requested more than once.

Finally the desired statistics for cacheability and traffic reduction are calculated as $1 - N_{obj}/N_{req}$ and Tr_c/Tr respectively. The virtual cache size is simply the value calculated in the previous step.

Ranges analytics

In the case of *Ranges*-based object identification, For each request the algorithm parses the request ID (as in *Size*, the ID is the concatenation of Object ID and advertised size), the timeslot, timestamp, start of the request (which is normally the first byte, but can be different in case of range requests), and end of the request (calculated as the sum of the start offset plus the effective size).

The requests are then grouped by ID and timeslot, and sorted by timestamp. After sorting, the timestamp is not needed any longer and is thus dropped. Sorting is important to accurately calculate the cache hits. Each slot will therefore contain all the requests for a specific object in a specific timestamp, with ID and timeslot as key, and the list of pairs $(start, end)$ as value.

For each slot, several statistics are calculated: the number of requests for that object in that timeslot, which is simply the length of the list; the total traffic generated by that object, calculated as the sum of the length of each request; the number of hits, calculated as the number of requests for the object that overlap at least partially with previous requests for the same object; and the size, calculated as the number of unique distinct bytes.

The elements are now grouped by timeslot only: the timeslot is once again the key, and the value is a list of tuples, one for each object in the timeslot, with the values calculated in the previous step. The final statistics are now calculated, similarly to the

other algorithms. The number of hits, the number of requests and the total traffic are all calculated by summing the respective per-object values. Cacheable traffic and virtual cache size are calculated as the sum respectively of traffic and size of the objects with at least one hit.

Finally the desired statistics for cacheability and traffic reduction are calculated as $1 - N_{hit}/N_{req}$ and Tr_c/Tr respectively. The virtual cache size is simply the value calculated in the previous step.

5.3 Results

In this section we report benchmarks of the analytics, mostly focusing on computational and memory complexity. We first illustrate the coding simplicity vs computational overhead tradeoff by comparing ANSI C, PIG and Map-Reduce implementations. We then optimize the running time of the most accurate and complex algorithm (Ranges), using compression and binary comparators. We finally illustrate results of the analytics.

5.3.1 Coding Simplicity vs Computational Overhead Tradeoff

As stated earlier, a natural tradeoff arises between the amount of control on a specific tool and the expected level of performance optimization that the tool allows. On the one extreme, we have total control over our low-level ANSI C implementation: while in this case it is easy to optimize for memory, and for performance on a single core, however we are limited to serial operations and face a computational complexity bottleneck. On the other extreme, PIG allows for very simple declarative-like queries over large datasets that benefit from parallel execution. This allows to express some of our analytics very compactly, with however a loss of control on the execution workflow, that is delegated to the PIG interpreter. In the middle, the Java Hadoop implementation retains a certain amount of control, and hence an expectedly lower overhead (provided that the analytics design is sound), with the added benefits of parallel execution. In this execution, we employ 255 mappers and 100 reducers.

The above tradeoff appears very crisply in Tab. 5.2, which shows a comparison of computational and memory complexity of serial (ANSI C) vs parallel (PIG and Java Map-Reduce) implementations of our analytics. Specifically, in the serial case we contrast the simplest vs the most complex algorithm, while we only consider the simple algorithm for the parallel case, for now. The table reports both the absolute performance, as well as the relative performance with respect to the ANSI C implementation of *ObjectID*

Table 5.2: Comparison of computational and memory complexity of serial (ANSI C) vs parallel (PIG and Java Map-Reduce) implementations of our analytics. Ratios in brackets are relative to the ANSI C implementation of *ObjectID* used as a reference: thus, ratios smaller (larger) than one correspond to performance gain (loss).

	Serial implementation		**Parallel implementation**	
Method	ObjectID	Ranges	ObjectID	ObjectID
Language	ANSI C	ANSI C	PIG	Java Map-Reduce
Runtime	25min	62min	38min	4min
	–	(1.8×)	(1.5×)	(0.16×)
Memory	8GB	12GB	n.a.	300GB
	–	(1.5×)	–	(37×)

used as a reference: thus, ratios smaller (larger) than one correspond to performance gain (loss). Notice that the serial vs parallel ratios are to be interpreted as *qualitative* as opposite to quantitative comparison: indeed, execution happens on hardware with similar, albeit not identical configuration.

At the same time, this qualitative comparison allows to gather very useful lessons. First, notice that despite parallel execution, the overhead of *ObjectID* in PIG appears to be so large that results computation [1] takes longer in the cluster than on a single-core serial execution. It follows that an implementation of more complex algorithms in PIG does not seem to be worth pursuing further for our analytics.

Second, notice that Map-Reduce implementation largely benefits of parallel execution, with running time that reduces to almost one order of magnitude (0.16×) with respect to serial execution in the simplest object identification case. At the same time, notice that the Map-Reduce framework does consume a considerable amount of memory: while this is not a critical issue (since, provided that there is enough memory, the jobs complete faster), it could be potentially an issue depending on the load of the cluster (i.e. the amount of jobs and their memory requirements as well). It follows that we expect Map-Reduce to be worthwhile investigating also for more complex algorithms.

5.3.2 Illustration of Map-Reduce Workflow

We now closely look the execution pattern of our Map-Reduce implementation. For the sake of illustration, Fig.5.7 reports a waterfall diagram of the execution time of one

1. Note that we do not report memory consumption as this is not clearly available with our account rights in the cluster

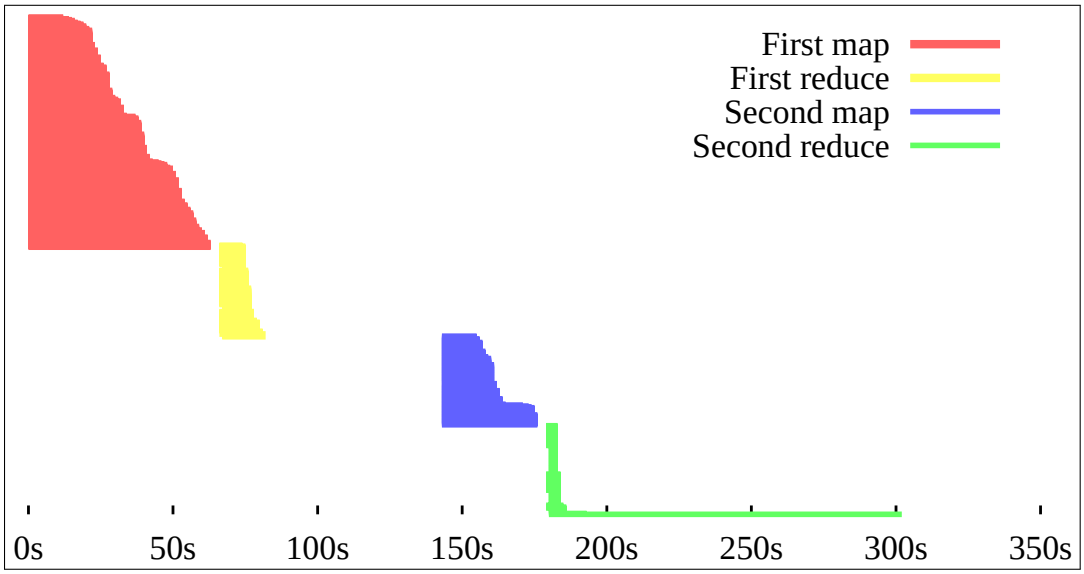


Figure 5.7: Waterfall diagram of a run of the Map-Reduce jobs for *Ranges*

run of the most complex analytics, i.e. *Ranges*. Map-Reduce phases in the waterfall use color codes that are consistent with those used in the previous section.

Several takeaways can be summarized from the picture. First, notice that the *overall execution time* of the complete workflow remains of the same order of magnitude that those shown in Tab.5.2 for the simplest algorithm (*ObjectID*). This is striking, especially since our optimized ANSI C implementation suffered a runtime degradation of about a factor of two: implicitly, this testifies the existence of a *non-negligible overhead* in the Map-Reduce system that not only affects the memory complexity (as per Tab.5.2), but also the computational complexity. At the same time, this overhead is only apparent for relatively simple tasks, but it gets diluted for more complex operation (at least for our analytics). This is especially reassuring, as the runtime reduction (With respect to *ObjectID* ANSI C implementation) stays at about 0.16× in the Map-Reduce implementation for both *ObjectID* as well as *Ranges* (i.e., no additional overhead for more complex operations).

Second, consider the *footprint and duration of each Map-Reduce phase*. In terms of footprint, the number of job in the first phase is correlated with the mappers (255) and reducers (100). Since the mapping in the second phase is the identity function, it follows that the number of parallel executed jobs remains 100 in the second phase. In terms of duration, notice that there is a non marginal variability of job duration in the first map phase (red color), with execution time of individual jobs distributed in the [10,60]sec

range. The first reduce phase (yellow color) starts immediately after the first map ends, and individual jobs complete faster, yet writing to disk delays the start of the second phase. This can be seen as a pause happening between the [70,140]sec range.

Job footprint in the second map phase (blue color) are, as we commented, limited to 100, with duration that span in a [10,20]sec range in most of the cases, with a significant fraction however finishing after about 30sec. Finally, the second reduce phase starts (green color); in this phase, there is actually a single reducer doing actual computation to consolidate all records in overall cacheability analytics over all clients and timeslots. It follows that 99 out of 100 jobs complete in less than 5 seconds, whereas the 100th job lasts for about 120sec. Overall, the duration of this specific execution for *Ranges* is 300sec, very much in line with simpler object identification techniques of *ObjectID*, but with the added benefit of increased accuracy.

5.3.3 Optimizing Map-Reduce Running Time

While these observation are insightful about the general pattern, they are not statistically representative of the expected running time. To optimize our workflow in a statistically significant results, we proceed as follows. We first let the system collect a large enough dataset (30 days), and then process this dataset (2 runs for each day) under different system-level optimization. By optimization we essentially mean two technical solutions: (i) implementation of a binary comparator and (ii) use of compression to store intermediate values. An important and aspect worth pointing out is that our analytics are run in the production cluster and have an operational value, we preferred to run batches of tests during the month of August 2015, when the amount of traffic is lower than the rest of the year: as traffic level is lower than average, caching is thus less interesting to absorb excess traffic and we can afford losing one month worth of data.

As for (i), recall that the sorting is performed on the keys, which are objects. Normally the Hadoop system would deserialize the incoming objects to compare them, which is a time consuming activity. For this reason we decided to write a raw comparator to compare the serialized keys, thus skipping the costly Java object deserialization step. This means that the raw comparator must parse the bitstream of the serialized keys, which is not a trivial task, but it apports speed advantages.

As for (ii), given the amount of intermediate data that needs to be written to disk between the two map-reduce jobs, compression may seem an interesting option: by compressing the data, the amount of data that has to be written to disk reduces (i.e. the gap between the first and second phase), and the writing time to disk may reduces

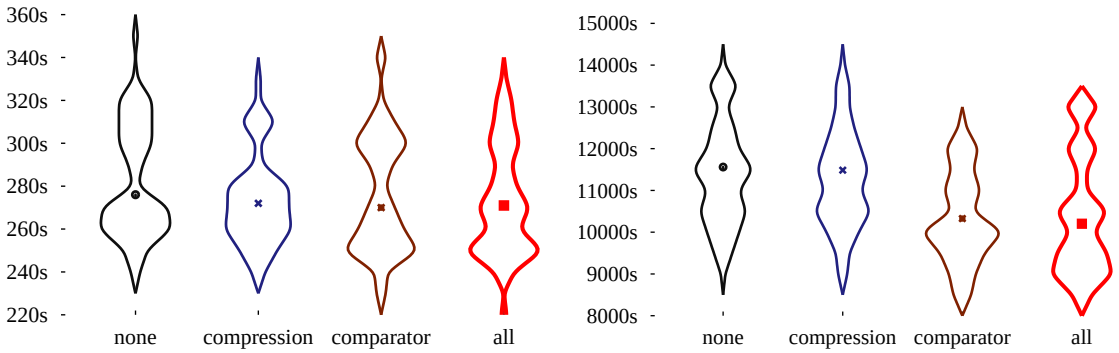
Table 5.3: Average Map-Reduce statistics for daily dataset processing with Ranges identification, and several optimizations (compression, binary comparator and combination thereof)

	Optimization			
	None	**Compression**	**Comparator**	**Both**
HDFS disk read	66.5GB	65.6GB	66.5GB	65.6GB
HDFS disk written	1.5GB	630MB	1.5GB	630MB
Map tasks	255	255	255	255
Reduce tasks	100	100	100	100
Map input records	$250 \cdot 10^6$	$250 \cdot 10^6$	$250 \cdot 10^6$	$250 \cdot 10^6$
Cumulative CPU time	154 min (2.57 h)	165 min (2.74 h)	147 min (2.46 h)	146 min (2.43 h)
RAM used	301GB	300GB	291GB	291GB
Real time	4.08 min	4.06 min.	3.95 min	3.81 min
Speedup factor	37.7	40.6	37.3	38.6

as well. At the same time, compression takes some amount of CPU time, hence it is not obvious to forecast the amount of gain in the overall execution time. Well aware of this tradeoff, we decide to compress the data using Snappy, a fast compression algorithm developed by Google. The reason we select Snappy, despite there being many other compression algorithms with better compression ratios, is precisely its light footprint: indeed, spending too much time compressing the data would ultimately counter the gains of having less data to write to storage. According to our preliminary tests, Snappy is even faster than LZO or Gzip with the fastest settings. On the other hand, it has a worse compression ratio, generally data compressed with Snappy is 20% to 100% bigger than with other algorithms. While compression speed is similar to LZO, decompression is a lot faster; compared to Gzip, instead, Snappy is about one order of magnitude faster. Finally, due to license issues, Snappy is easily found in most Hadoop deployments, whereas other libraries must always be installed manually.

Details of this benchmark are reported in Tab.5.3 and Fig.5.8. Specifically, the table reports the average values over 30x2 experiments per each configuration; the amount of resources are referred to process one timeslot of one day: it can be seen that, while the total computational time across all cores is very high (some hours), the real-time duration is very small (few minutes), therefore enabling almost interactive analysis of the traffic.

Fig.5.8 additionally reports details about the most interesting performance indicators, namely the duration of the whole process Fig.5.8-(a) as well as the cumulative CPU



(a) Real time (b) CPU time

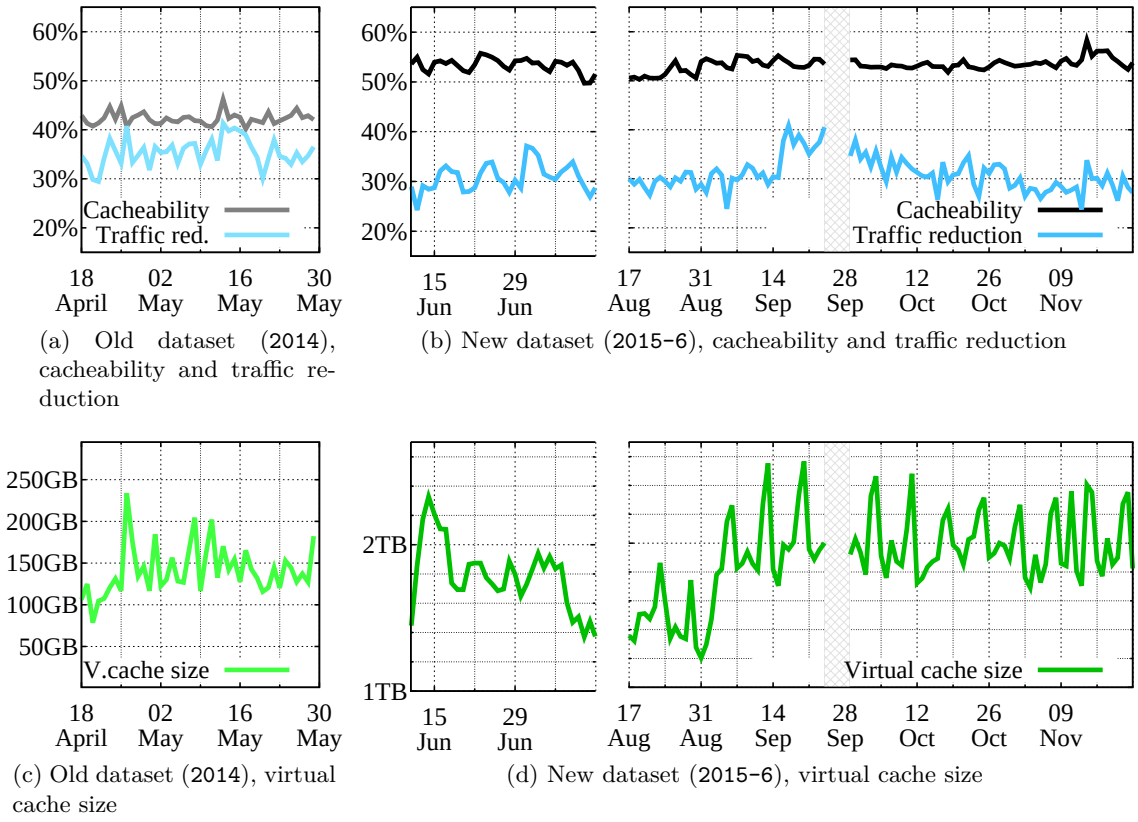
Figure 5.8: Violin plots of real time (a) vs cumulative CPU time over all cores (b) for the Ranges identification. Notice a consistent reduction in the cumulative CPU time (nearly 1000secs), to which however corresponds only a marginal gain when both optimization are in use.

time over all jobs Fig.5.8-(b). The duration of the process is useful from the viewpoint of users of these analytics, while the cumulative CPU time is useful from the viewpoint of the cluster maintainer. For instance, we expect compression to potentially reduce the overall duration, at the price of an increase of the cumulative CPU time. Statistics in Fig.5.8 are reported as violin plots: the shape of the violin is the PDF of the statistics of interest, which is made symmetric in the visualization (i.e., the area of each violin equals to twice the area under the PDF, hence 2 by definition). The violin also report the median reference as a point in the plot.

Enabling both (i)+(ii) optimizations, one can notice a consistent reduction in the cumulative CPU time (nearly 1000secs), to which however corresponds only a marginal real-time gain when both optimization are in use. This is due to the fact that compression has a very limited impact on the runtime: the disk bottleneck is *reading* the input, the amount of intermediate *writing* amount saved by using compression is less than 3%, hence a marginal improvement. Using the binary comparator, instead, brings some clear advantage in the cumulative time: at the same time, the gain spread over all jobs reduces in the overall duration, where as we have seen there exist correlation between phases, so that reducing the average job duration helps only in part.

5.3.4 Analytics Output

Finally, we illustrate the output of the analytics gathered in the operational network with our automated workflow. While the analysis of these results is not the main topic



(a) Old dataset (2014), cacheability and traffic reduction

(b) New dataset (2015-6), cacheability and traffic reduction

(c) Old dataset (2014), virtual cache size

(d) New dataset (2015-6), virtual cache size

Figure 5.9: Illustration of the analytics on the [4] dataset (2×1Gbit/s, 42 days) along with the results calculated for the new dataset (2×10Gbit/s, 132 days; Note the two interruptions in the plot: the August interruption is a voluntary one to perform the benchmarks and the MapReduce workflow tuning, the October one is due to a small hardware issue on the probe.

of this work, we believe to be important to provide at least a brief comment. Indeed, the side effect of this work is precisely of being able to peek into larger datasets, so that comparing new vs established results[74] is what this work enables.

The plots in Fig.5.9 report execution of the serial analytics on the [4] dataset (2×1Gbit/s, 42 days) alongside with the results of the parallel MapReduce analytics computed over the the new dataset (2×10Gbit/s, 132 days). Top plot reports the cacheability (black line) and traffic reduction (blue line), while bottom plot reports the virtual cache size (green line). Note the two interruptions in the plot: the August interruption is a voluntary one to perform the benchmarks and the MapReduce workflow tuning, the October one is due to a small hardware issue on the probe. Notice that cacheability and traffic reduction remain into close ranges: cacheability jumps from slightly more than 40% in

the 1Gbps dataset to slightly more than 50% in the 10Gbps dataset; similarly, traffic reduction decreases from slightly more than 30% to slightly less than 30%.

Conversely, the virtual cache size required to attain these caching performance significantly increases, by more than one order of magnitude, jumping from over 100GB to over 2TB. In this scenario, the ability to serve at 10Gbps line rate, with caches that are for reasons of costs cannot be entirely made of DRAM storage becomes of primary importance, reinforcing the need of designs such as [73].

5.4 Summary

In this chapter, we showed how to exploit a MapReduce cluster to continuously assess cacheability statistics gathered from passive analysis of traffic flowing on high-speed links in an operational network. Our main contributions are: (i) to motivate the use of a parallel and horizontally scalable workflow; (ii) to design parallel analytics in PIG and MapReduce; (iii) to experimentally compare serial vs parallel analytics, as well as PIG vs MapReduce; (iv) to perform a thorough benchmarking and optimization of our MapReduce workflow.

We have also shown that, by using Hadoop and a native Java MapReduce implementation, a speedup greater than a factor 6 is achievable, in comparison with a serial ANSI C implementation. This achievement enables the analysis of datasets that are by far larger than what done in the community so far – where by far means over 10× in duration, 10× in the number of requests and 10× in the distinct objects with respect to the largest dataset analyzed in the available literature. Given the horizontal scalability of Hadoop MapReduce, we expect these analytics to be future proof –i.e., scale further in space, time or line rate– at no additional cost.

Chapter 6

Conclusions and perspectives

In this chapter we summarise the goals achieved in this thesis, the implications they have for the current network operators, and we provide a perspective on possible future research.

6.1 Summary

First, in Chapter 3, we illustrated the methodology used to capture the traffic traces used in this thesis, including a detailed overview on the design and implementation of the high-performance software tool used. We also introduced the metrics used to measure the amount of traffic or requests that can be saved, the network topology where the probe running our tool was placed, and some details about the characteristics of the traces themselves.

Then in Chapter 4 we analysed the traffic traces. First we determined that a timescale of one day is ideal, and then used the traces to simulate three scenarios, with caches in the backhaul, at the cusomer's home router, or both. The metrics introduced previously give us the upper bound of about 40% of the requests and 30% of the traffic that can be cached. From those results we calculated the lower bound of the cache sizes needed; we found that the lower bound for a cache in the backhaul is 100GB, and 100MB for a cache at the customers' home routers. We then performed a simulation with an LRU cache, in order to validate the results. We found out that a real cache sized according to the ideal values can save around 10% less traffic and requests compared to the ideal cache, while a cache sized 10 times bigger achieves the theoretical performance.

Finally in Chapter 5 we dealt with the problem of scaling up the analysis of the traces using a Hadoop. We compared the performances and the limitations of a classical

C implementation with a Hadoop implementation of the analytics, both using the PIG query language and using directly MapReduce. We found out that the most scalable solution for our usecase is using MapReduce directly.

6.2 Conclusions

The main result of this thesis is that caching in the access and backhaul network yields clear advantages to ISPs, customers and content providers, and it is fasible with current technology.

The traffic reduction in the access network translates directly into a reduction of outgoing traffic, and therefore it represents a concrete and obvious saving for the operators. But the most important saving is in the backhaul link from the access network to the core. Those links are usually the bottleneck in both fixed and mobile networks, and very often it's not technically or economically feasible to upgrade them once they saturate. A traffic reduction on the backhaul links would therefore free up bandwidth that can be then used to provide access to more customers, thus benefiting both the additional customers that will have access, and the providers that will see additional revenue with the same infrastructure. The customers will also have a gain in speed due to the fact that the requests will be serviced closer to them. The content providers will see their content delivered faster and to an increased amount of customers, and at the same time less traffic will actually hit their servers, thus increasing the performance of the requests that couldn't be cached.

Another very important and striking conclusion that we can draw is that caching in the access network is already feasible with current technology. 100 GB of fast DRAM are relatively cheap and can fit in any small rack-mount server, and 100 to 1000 MB of RAM can be easily built into a home router. Some home routers actually already come with that much ram, so in that case it would be just a matter of modifying the firmware so as to allow caching.

6.2.1 Transparent Web caching and encryption

As mentioned in Sec.5.1.2, the usage of encryption in the Internet is growing steadily and is also endorsed by recent IETF IAB recommendations. HTTP 2.0 draft [75] currently under discussion in the HTTPbis IETF working group specifies encryption by default by using TLS 1.2 and following versions [76]. It is out of scope of this thesis to fully elucidate the trade-offs of using encryption in today's Internet, for which we refer

the reader to [77]. Yet, some architectural considerations are worth sharing concerning the technical challenges that an increasingly encrypted Internet will bring, and that CCN can gracefully solve.

TLS provides communications security for client/server applications and encrypts everything included in the TCP byte stream. The encryption service provided by TLS is not compatible with proxy or transparent caching, which is however a very important service successfully deployed to reduce bandwidth consumption in many network locations. Caching non encrypted Web traffic in proxies or transparent appliances is today implemented and optimized by using HTTP almost as a transport layer. An HTTP datagram has also been proposed in [1] to effectively implement almost all the functionalities CCN provides, with the exception of data encryption and security in general. It is clear that encrypted Web traffic, using TLS, can be cached only in the end points, i.e. the client Web browser, or application, and in content provider appliances. Of course this latter end point can be distributed in a CDN which manages the encryption on behalf of the content provider. Therefore caching encrypted Web traffic cannot be implemented as a transparent network primitive because it would always require the sender to delegate encryption to a third-party, e.g. a CDN. A minimum level of cooperation is required to guarantee inter-networking of communications primitives which are based on delegation. Datagram based packet-switched networks make use of delegation for data forwarding and routing – but other services like name resolution, as provided by the DNS, do require delegation as well. We believe that in-network data caching is an additional transparent network primitive that cannot be implemented without guaranteeing the required level of security and interoperability that TLS cannot provide.

6.3 Perspectives

6.3.1 Ecription and TLS/SSL

The significant potential gains we have measured do not apply to encrypted web applications (15% of the traffic in the first dataset, 30% in the second, and steadily increasing in time) which obviously cannot be transparently cached. It is clear that encrypted Web traffic, using TLS, can be cached only in the end points, i.e. the client Web browser, or application, and in content provider appliances. Of course this latter end point can be distributed in a CDN which manages the encryption on behalf of the content provider. Therefore caching encrypted Web traffic cannot be implemented as a transparent network primitive because it would always require the sender to delegate

encryption to a third-party, e.g. a CDN. A minimum level of cooperation is required to guarantee inter-networking of communications primitives which are based on delegation. Datagram based packet-switched networks make use of delegation for data forwarding and routing – but other services like name resolution, as provided by the DNS, do require delegation as well. We believe that in-network data caching is an additional transparent network primitive that cannot be implemented without guaranteeing the required level of security and interoperability that TLS cannot provide.

The clear solution is to use ICN, and in particular the CCN implementation, as the best fit technology to address all the drawbacks of currently available workarounds and providing caching as a transparent network primitive.

6.3.2 Mobile traffic

Another interesting development would be to measure the cacheability of mobile traffic, to assess the feasibility and performance of caches placed on the base stations. Due to its nature, mobile traffic behaves very differently from non-mobile one; in particular the amount of interrupted or incomplete requests is expected to be significantly higher. In order to perform such analysis, the capture software would probably need to be extended, and surely the current hardware setup wouldn't be adequate. Bureaucratic and logistical problems are also expected, since base stations are more difficult to reach.

6.3.3 Further improving the analysis

There are many more improvements that could be made to the analysis, some also requiring improvements in the caputre tool.

Proper state tracking of cookies would improve the accuracy of the analysis. This would require adding some fields in the output of the capture tool to provide the value of the cookies (or a hash thereof), and proper state tracking of cookies will doubtlessly increase the complexity of the analysis.

Another improvement could be to consider the caching directives when performing the LRU simulations. HTTP servers sometimes provide headers in the reply that indicate whether the object should be cached or not. This also requires to add some fields in the output of the capture tool; the amount of additional processing needed would be very low.

We have seen that properly accounting for partial content downloads increases the accuracy of the analysis. Some websites and services, especially video streaming, perform chunking on the application level, embedding the requested object ranges in the URL.

Since the base URL is different, the tool considers it as separate objects, whereas they should be considered as partial requests. An application-specific URL analyser would be needed to process the URL and extract the actual ranges; the additional load on the analysis step would be minimal, since range requests are already supported.

Appendices

Appendix A

HACkSAw configuration options

This appendix explains the available configuration options for HACkSAw. The name and possible values of each option is provided, together with a description of the functionality it affects. Unspecified values are assigned a default value, also provided here. Parameters specified on the commandline take precedence over the content of the configuration file. All numbers are to be specified as integer numbers.

Name	**Type**	**Default**	**Description**
`connection_timeout`	*minutes*	15	general timeout for closing inactive connections (0 = never close)
`ip.connection_timeout`	*minutes*	*connection_timeout*	timeout for IP connections
`tcp.connection_timeout`	*minutes*	*ip.connection_timeout*	timeout for TCP connections
`udp.connection_timeout`	*minutes*	*ip.connection_timeout*	timeout for UDP connections (streams)
`anon_ips`	*boolean*	yes	anonymize (hash) IP addresses and MAC addresses
`anon_ips.salt`	*integer*	0	salt to use when hashing to anonymise, 0 means random
`tcp.hashtable`	*integer*	1048576	size in elements of the TCP flow hashtable
`udp.hashtable`	*integer*	1048576	size in elements of the UDP flow hashtable

`tcp.enabled`	*boolean*	yes	enable processing of TCP
`udp.enabled`	*boolean*	yes	enable processing of UDP
`http.etags.as_id`	*boolean*	yes	append the value of ETAGs (when available) when calculating the object IDs
`http.hash_urls`	*boolean*	yes	hash HTTP URLs (**things will break if disabled**)
`http.use_dns_info`	*boolean*	false	Use and correlate information gathered by the DNS dissecter in the HTTP log
`hacksaw.log`	*path*	/var/log/hacksaw.log	log file, with status and debug information
`hacksaw.daemon`	*boolean*	no	start HACkSAw as a deamon
`hacksaw.autorestart`	*boolean*	no	autorestart the daemon if it crashes
`hacksaw.configfile`	*path*	/etc/hacksaw.conf	configuration file to use
`nthreads`	*integer*	1	number of concurrent processing threads
`input`	*string*	eth0	input file name, interface, or device node
`input.type`	*string*	pcap	input type. e.g. `pcap`, `pcap_file`, `dag`
`output.path`	*path*	.	path or base directory for the output
`output.type`	*string*	file	output type. e.g. `file`, `file.byend`
`output.slotsize`	*seconds*	1 day	slot size of the log files
`input.dag.mem`	*MiB*	512	total system RAM to allocate to the DAG card
`input.dag.path`	*path*	/usr/local/bin/	path where to find DAG binaries
`input.dag.streams`	*string*	hat	how to distribute packets in streams. (`hat`,`ports`)

`input.dag.stream`N`.ports` *string*	list of interfaces to put in the Nth stream, without separators, e.g. `01`

Appendix B

HACkSAw output files

This appendix describes the contents of the output files generated by HACkSAw. A short description is provided to explain the type of connection logged in each file, and then the fields are presented in the same order as they appear in the file, indicating the type of the value and the meaning.

Many fields have similar formats, so here is a description of the value formats used throughout all the files.

Number	An integer number, in base 10.
Hex	An integer number, in base 16.
Timestamp	Timestamp in UNIX time (number of seconds since Jan 1st 1970 UTC), with microsecond accuracy.
Hash	A 16-digits hexadecimal number, produced with the FNV1a hashing algorithm.
IP	An IP address, in dotted-decimal format.
MAC	A MAC address, in the traditional hex format with colons.
Port	A decimal number between 1 and 65535 representing a port number.
Conn-ID	A string in the format `Number:Number`, representing a unique connection ID. The first number is the ID of the thread, while the second is the unique connection ID inside that thread. In case a line is logged in the output file with no associated connection, the second number will be 0.
Bitfield[n]	A string of length n, each character indicating a binary value. The meaning of the characters is explained case by case.
String	A string, can not contain spaces, usually shorter than 30 characters.
Text	A string, can contain spaces and can be very long.

An asterisk (*) next to the type indicates that the field can be empty, in which case it

will contain a dash (`-`) instead of the value.

B.1 log_tcp_complete

This file logs all observed TCP connections, including incomplete ones. Since no text fields are present, so the fields are delimited by spaces.

Name	Type	Description
Conn-ID	*Conn-ID*	TCP Connection ID, used to correlate this connection with other L7 requests logged in other files
Protocol	*String*	L7 protocol detected, `?` if unknown
Client IP	*IP*	IP address of the source of the connection
Client Port	*Port*	Port number of the source of the connection
Server IP	*IP*	IP address of the destination of the connection
Server Port	*Port*	Port number of the destination of the connection
Client Packets	*Number*	Number of packets sent by the client
Server Packets	*Number*	Number of packets sent by the server
Client Bytes	*Number*	Number of bytes sent by the client
Server Bytes	*Number*	Number of bytes sent by the server
Start time	*Timestamp*	Timestamp of the first packet of the connection
Handshake time	*Timestamp*	Timestamp of the SYN/ACK packet, when the TCP three-way handshake is over
End time	*Timestamp*	Timestamp of the last packet of the connection

B.2 log_http_complete

This file logs all completed or interrupted HTTP connections observed. Each HTTP transaction (request/reply pair) is logged in a separate line. A Connection ID is provided to correlate requests belonging to the same TCP connection, and to correlate with the data in the `log_tcp_complete`. Since some of the fields can contain spaces, the fields of this file are separated by tabs.

Name	Type	Description
Client MAC	*MAC*	MAC address of the source of the connection

Dest MAC	*MAC*	MAC address of the destination of the connection, or of the first hop towards the destination, if the destination is not link-local
Client IP	*IP*	IP address of the source of the connection
Client Port	*Port*	Port number of the source of the connection
Server IP	*IP*	IP address of the destination of the connection
Server Port	*Port*	Port number of the destination of the connection
Conn-ID	*Conn-ID*	TCP Connection ID, used to correlate the requests from this file with the ones in `log_tcp_complete`
Version	*String*	HTTP version string (e.g. `HTTP/1.1`)
Method	*String*	HTTP method (e.g. `GET`)
Request time	*Timestamp*	Timestamp of the first packet of the HTTP request
Request headers	*Number*	Size of the request headers, in bytes
Object	*Hash*	Hash of the concatenation of object URL and, if available, ETAG
ETAG	*String**	Indicated the presence of the ETAG header
Cookies	*Bitfield[2]*	`c/-` client side cookies present/not present `s/-` server side cookies present/not present
Reply code	*Number*	HTTP response code (e.g. `404`)
Reply headers	*Number*	Size of the reply headers, in bytes
Content-Length	*Number**	Object size as advertised by the `Content-Length` header
Actual length	*Number*	Object size as observed
Range	*Text**	Raw value of the `Range` header, in case of range requests
Reply headers time	*Timestamp*	Timestamp of the first packet of the HTTP reply
Reply content time	*Timestamp*	Timestamp of the first packet of the HTTP reply containing the requested object. Will be 0 if no object is returned.
Reply end time	*Timestamp*	Timestamp of the last packet of the HTTP reply containing the requested object. Will be 0 if no object is returned.
Transfer-Encoding	*String**	Content of the `Transfer-Encoding` header

Hostname	*String*	Content of the `Host` header, or the IP address of the server if no `Host` header is present
Content-Type	*String**	MIME type of the returned object, if any, as indicated by the `Content-Type` header
Client headers	*Hex,String*	Hexadecimal bitfield. Each bit represents the presence of a specific frequently used header in the client request. Headers not present in the list are concatenated to the value, separated by commas.
Server headers	*Hex,String*	Hexadecimal bitfield. Each bit represents the presence of a specific frequently used header in the server reply. Headers not present in the list are concatenated to the value, separated by commas.
DNS request	*Timestamp*	Timestamp of the DNS request used to resolve the domain for this connection. Only present if DNS logging is active, DNS result sharing is active, and DNS request were performed within a reasonable (configurable) timeframe. It will be 0 otherwise.
DNS reply	*Timestamp*	Timestamp of the DNS reply used to resolve the domain for this connection. Only present if DNS logging is active, DNS result sharing is active, and DNS request were performed within a reasonable (configurable) timeframe. It will be 0 otherwise.
User-Agent	*Text*	Content of the `User-Agent` header. Can be very long.

B.3 log_udp_complete

This file logs all observed UDP sessions, including incomplete ones. Since no text fields are present, so the fields are delimited by spaces.

Name	Type	Description

Conn-ID	*Conn-ID*	UDP Connection ID, used to correlate this connection with other L7 requests logged in other files
Protocol	*String*	L7 protocol detected, `?` if unknown
Client IP	*IP*	IP address of the source of the connection
Client Port	*Port*	Port number of the source of the connection
Server IP	*IP*	IP address of the destination of the connection
Server Port	*Port*	Port number of the destination of the connection
Client Packets	*Number*	Number of packets sent by the client
Server Packets	*Number*	Number of packets sent by the server
Client Bytes	*Number*	Number of bytes sent by the client
Server Bytes	*Number*	Number of bytes sent by the server
Start time	*Timestamp*	Timestamp of the first packet of the connection
End time	*Timestamp*	Timestamp of the last packet of the connection

B.4 log_dns_complete

This file logs all completed or interrupted HTTP connections observed. Each HTTP transaction (request/reply pair) is logged in a separate line. A Connection ID is provided to correlate requests belonging to the same TCP connection, and to correlate with the data in the `log_tcp_complete`. Since some of the fields can contain spaces, the fields of this file are separated by tabs.This file logs all observed DNS requests, including incomplete ones. Since no text fields are present, so the fields are delimited by spaces.

Name	Type	Description
Thread-ID	*Number*	Thread ID, used for debugging purposes
Client IP	*IP*	IP address of the source of the connection
Client Port	*Port*	Port number of the source of the connection
Server IP	*IP*	IP address of the destination of the connection
Server Port	*Port*	Port number of the destination of the connection
Transaction ID	*Hex*	Transaction ID as per DNS protocol
Request time	*Timestamp**	Timestamp of the DNS request
Opcode	*Number*	DNS request opcode

Request Flags	*Bitfield[7]*	`R/Q` packet is a response/query `A/-` server is authoritative/or not `T/-` is truncated/or not `r/-` recursion is wanted/or not `R/-` recursion is available/or not `a/-` reply is authenticated/or not `u/-` non authoritative replies accepted/or not
Request Questions	*Number*	Number of question records in the question section of the request
Request Answers	*Number*	Number of answer records in the answer section of the request
Request Authorities	*Number*	Number of name servers records in the authorities section of the request
Request Additionals	*Number*	Number of additional records in the additional section of the request
Request Class	*String*	DNS class of the request. Usually INET.
Request Types	*String*	Types of record requested. It is a comma separated list of all the record types present in the question records
Request IPv4	*String**	List of domains whose IPv4 address is requested (record type A)
Request IPv6	*String**	List of domains whose IPv6 address is requested (record type AAAA)
Request MX	*String**	List of domains whose mailserver address is requested (record type MX)
Request NS	*String**	List of domains whose NS addresses are requested (record type NS)
Reply time	*Timestamp**	Timestamp of the DNS reply
Opcode	*Number*	DNS request opcode
Reply Code	*Number*	DNS reply code
Reply Flags	*Bitfield[7]*	Same meaning as the *Request flags* field
Reply Questions	*Number*	Number of question records in the question section of the request
Reply Answers	*Number*	Number of answer records in the answer section of the request

Reply Authorities	*Number*	Number of name servers records in the authorities section of the request
Reply Additionals	*Number*	Number of additional records in the additional section of the request
Reply Class	*String*	DNS class of the request. Usually INET.
Reply Types	*String*	Types of record requested. It is a comma separated list of all the record types present in the question records
Reply IPv4	*String**	List of IPv4 addresses whose resolution was requested
Reply IPv4 TTL	*String**	List of TTL values for the IPv4 addresses in the reply
Reply IPv6	*String**	List of IPv6 addresses whose resolution was requested
Reply MX	*String**	List of mailserver domains for the requested domain
Reply NS	*String**	List of DNS names or addresses for the requested domain

Appendix C

Presentation of the results

The web-based presentation infrastructure, described in this appendix, was developed by Wuyang Li, and not by the author, at the same time this PhD was taking place; it is included here for reference and completeness. The presentation infrastructure is a web-based system that allows authorised people to have fast and easy access to the graphs of the cacheability and traffic reduction statistics calculated using hadoop.

Workflow

As illustrated in fig.1.2 in Chapter 1, the workflow is rather straightforward: the data is collected by the probe, sent to the hadoop cluster for analysis, and then sent to the presentation website for display. The website is necessary to have a rapid sight on the results of the tool, to check that no data is missing due to network problems on the (slow) control link, and to extract nice graphs to be used in scientific publications. Figure C.1 shows a screenshot of the main page of the website. The controls to select the time granularity and the dates to show are also visible.

The data is inserted directly into a database, the webserver performs some database queries to extract the relevant values to show when interrogated by a web browser.

Technologies

The web server used is Node.js, as it provides superior performance in presence of bursts of requests, such as the ones generated by the frontend. It is also easier to interface client-side javascript libraries with a javascript server.

The database used is MySQL, since only a few simple tables are needed. On the other hand, those tables need to be accessed quickly, and at arbitrary positions. The

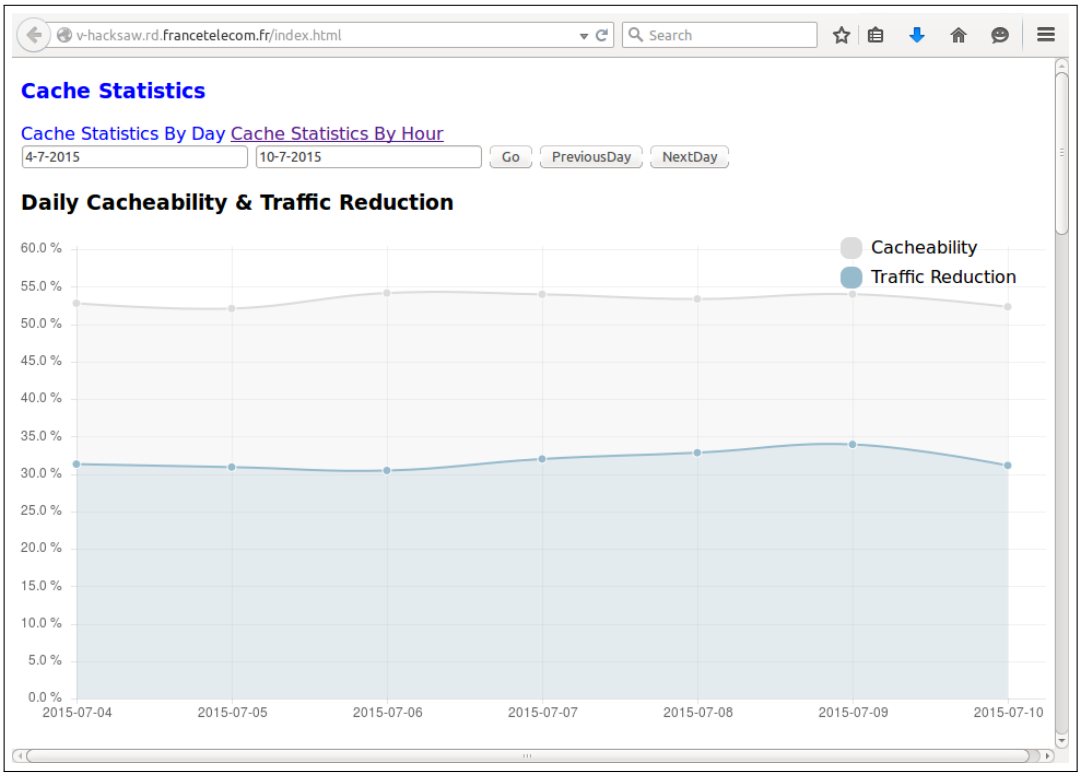


Figure C.1: Screenshot of the first page of the webpage.

libraries used also expect to find the data in a database.

The webpage itself is written in HTML5, and uses the Chart.js and GoogleChart libraries to display the graph. The interaction between the webpage isself and the backend is performed through AJAX (Asyncronous Javascript And XML), in order to provide a smooth and modern experience to the user.

Frontend and backend

The backend, written in javascript, makes heavy use of asynchronous event-driven callbacks, in order to improve the response times and the overall performance. The MySQL database has a table for each available time granularity (one day and one hour); each row represents all the relevant statistics for that timeslot, indexed by timestamp. The server software itself is composed of 4 different javascript files implementing the main module, the HTTP server, the SQL request handler, and the glue to connect everything together.

The frontend of the system is the webpage, which interacts with the server using

asynchronous AJAX requests, with the requested datapoints for each of the statistics shown in the page. Changing the dates causes new AJAX requests to be sent to the server, and the graph is updated smoothly. For convenience, there are buttons to go one day back or forward.

The statistics displayed, in four separate graphs, are:

— Cacheability
— Traffic reduction
— Virtual Cache Size
— Share of HTTP vs HTTPS connections
— Distribution of the content popularity

Cacheability and Traffic reduction are plotted in the same graph (as shown in the screenshot in Fig.C.1), since they use the same scale (percentage), while the other statistics all have distinct graphs.

Appendix D

Synthèse en français

Introduction

Le trafic internet aujourd'hui monte en flèche, et de plus en plus est servi par le WEB en utilisant HTTP. Un nombre croissant de personnes utilise une quantité croissante de dispositifs connectés, lesquels, à cause du progrès technologique, ont une quantité croissante de bande passante à disposition. Le nombre de connexions 2G décroît en faveur de connexions 3G et 4G, et dans quelques ans les connexions ultra-rapides 5G seront disponibles pour les consommateurs.

Cette augmentation de bande passante disponible a stimulé la creation et/ou expansion d'applications à usage de bande intensive, comme le VoD (Video on Demand – vidéo à la demande) et le SVoD (Subscription Video on Demand – vidéo à la demande en abonnement), comme Netflix et YouTube. Naturellement beaucoup de services ont aussi apparu qui n'utilisent pas beaucoup de bande passante, par example le partage de fichier ou VoIP (Voice over IP – voix sur IP), mais puisque ils ne constituent que une partie marginale du trafic total, et ils ne sont pas normalement servi par HTTP, ils ne sont pas relevants pour cette thèse.

Le streaming vidéo donc constitue une énorme partie du trafic internet, et alors que dans le passé ces services utilisaient des protocols proprietaires (comme RTP ou RTSP), aujourd'hui le streaming est réalisé presque exclusivement sur HTTP. Selon des prévisions de Cisco, en 2019 80% du trafic internet sera du au streaming vidéo.

La propagation de solutions de livraison de contenus basées sur le Web a plusieurs causes (par example flexibilité avancé et facilité d'accès depuis une varieté de dispositifs, pour la plupart mobiles) et conséquences. Notamment, aujourd'hui les clients du vidéo à la démande en abonnement (SVoD) exigent une haute qualité perçue en accèdent au

videos depuis tout dispositif dans et dehors leurs maisons (TV, HDTV, smartphones, tablettes, lecteurs multimédia).

Les CDNs (Content Delivery Network – Réseau de Diffusion de Contenu) ont été créés à la fin du 20ème siecle pour ammeliorer les prestations des sites web géographiquement loins. L'idée de base est simple: disséminer des caches partout dans le monde, aufin d'avoir toujours des caches suffisament proches aux utilisateurs. Les utilisaterus sont dirigés vers une cache proche selon leur location. Les operateurs du CDNs obtiennent des revenues des propriétaires des sites qui utilisent leurs reseaux. Cette idée, initiallement conçue pour ammeliorer les prestations des sites utilisés par les clients finaux, cause aussi una réduction du trafic dans le reseau fédérateur.

aujourd'hui, des liens intercontinentaux vites permettent d'avoir accès presque instantané à quelconque site web dans le monde, réduisant donc l'impacte de leur tâche initiale. Les CDNs ont quand même evoluè pour fournir des services supplémentaires, et donc ils sont encore rélevants.

Du premier façon, les CDN fournissent une haute disponibilité, même en cas de trafic massif, parce que les serveurs d'origine (celles où les contenus sont hébergés) ne recevront que une petite partie des requêtes. Ça permet aux éditeurs d'utiliser des serveurs petits (et donc pas chers), et de les gérer directement. Beaucoup de caches partout dans le monde aide aussi contre les attaques DDoS (Distributed Denial of Service – Attaque par Déni de Service Distribuée), parce que plusieurs clients distribués géographiquement qui essayent d'attaquer le même serveur attaqueront en fait differentes caches.

Les operateurs CDN les plus grands placent leur caches aujourd'hui directement dans les réseaux des fornisseurs d'accès Internet, aufin de minimiser la latence, même en payant les fornisseurs pour l'hébergément.

Les advantages des CDN causent aussi une reduction du traffic dans les reseaux centraux, et donc des économies pour les operateurs des sites web, parce que ils doivent moins payer pour le trafic; pour les fornisseurs d'accès internet, parce que leur reseaux necessiteront des moins de mises à jour; et finalement pour les operateurs des CDN, parce que ils sont payés pour leurs services.

Mais, même placés dans les reseaux des fournisseurs d'accès, les caches des CDNs sont très grandes et servent des centaines de milliers ou même des millions des utilisateurs.

Puisque les CDNs permettent d'économiser trafic, les ISP mêmes ont commencé à dépolyer leurs CDNs; les CDNs gérées par les ISP sont généralement utilisées pour VoD, SVoD et télédiffusion. Le multicast IP traditional ne satisfait pas touts les besoins: le multicast est uniquement sur UDP, et donc pas fiable et sans contrôle de la congestion, et, en fin, le multicast très souvent n'est pas configuré correctement, et un seul nœud

configuré incorrectement est assez pour le rendre inutile. Pour ça les ISP utilisent des systèmes CDN.

Le modele d'aujourd'hui presente plusiers faiblesses, parce que il s'appuie sur tierces (par example Netflix) pour fournir des services web, dont la qualité depends du reseau de quelq'un d'autre (les ISPs). Pour les services vidéo-centriques, la relation entre investissements et revenues tend à être déséquilibré quand des fournisseurs de contenus tiers ne généront pas de revenues supplementaires aux ISPs, qui, par contre, doivent prendre en charge les côutes d'invesitssement et operationels pour livrer trafic supplemetaire sans une augmentation du revenue. Le client ne veut pas payer plus pour résoudre le conflit entre les deux. Le conflit entre Netflix, Comcast, Verizon et AT&T aux États Unis est un bon example.

Les ISPs sont donc confrontés avec un dilemme: augmenter la capacité vers les fournisseurs du contenu, prenant en charge les côuts, ou fournir un service sous-pair aux clients, causant des plaintes et possiblement des actions en justice.

Puisque le trafic web est la plus grand part du trafic internet total, le paradigme classique point-à-point est suboptimale. Une solution meilleure, en prenant inspirations des CDNs, est ICN (Information Centric Networking – Reseaux Centré sur l'Information).

L'idée fundamentale de ICN est que le contenu est l'unité de base; le paquets dans le fils sont contenus ou requêtes pour contenus specifiques. Il n'y a pas de connexions entre l'utilisateur et le serveur, mais seulement des requêtes envoyée dans le reseau, et des reponses avec les objets démandés. Chaque routeur a une petite cache (appellé Content Store – Stockage de Contenu); ça permet de cacher les objets les plus populaires dans locations dans le reseau où ils sont necessaires. Ça permet la création de reseaux à maille et/ou reseaux tolerantes aux retards.

Un réseau global de caches est comme une énorme CDN qui sert tous les sites; le contenu populaire sera probablement proche des utilisateurs, les serveurs d'origine evitent la majeure partie du trafic (donc traitant trafic élevé ou DDoS automatiquement). Les differences avec les vraies CDNs sont:

— moins de contrôle: ICN ne donne pas contrôle aux originateurs du contenu sur la location où le contenu sera caché
— taille: la plupart des caches seront petites, surtout proche du bord du reseau; ça peut être inefficace
— pas plus de CDNs: chaque objet est caché dans le reseau par le reseau même, donc il n'y a pas plus de raisons pour l'existence des CDNs

Ça est effectivement un grand changement de paradigme, comme celui de reseau à circuit vers reseau à commutation de paquets, et il necessite de énormes changements dans

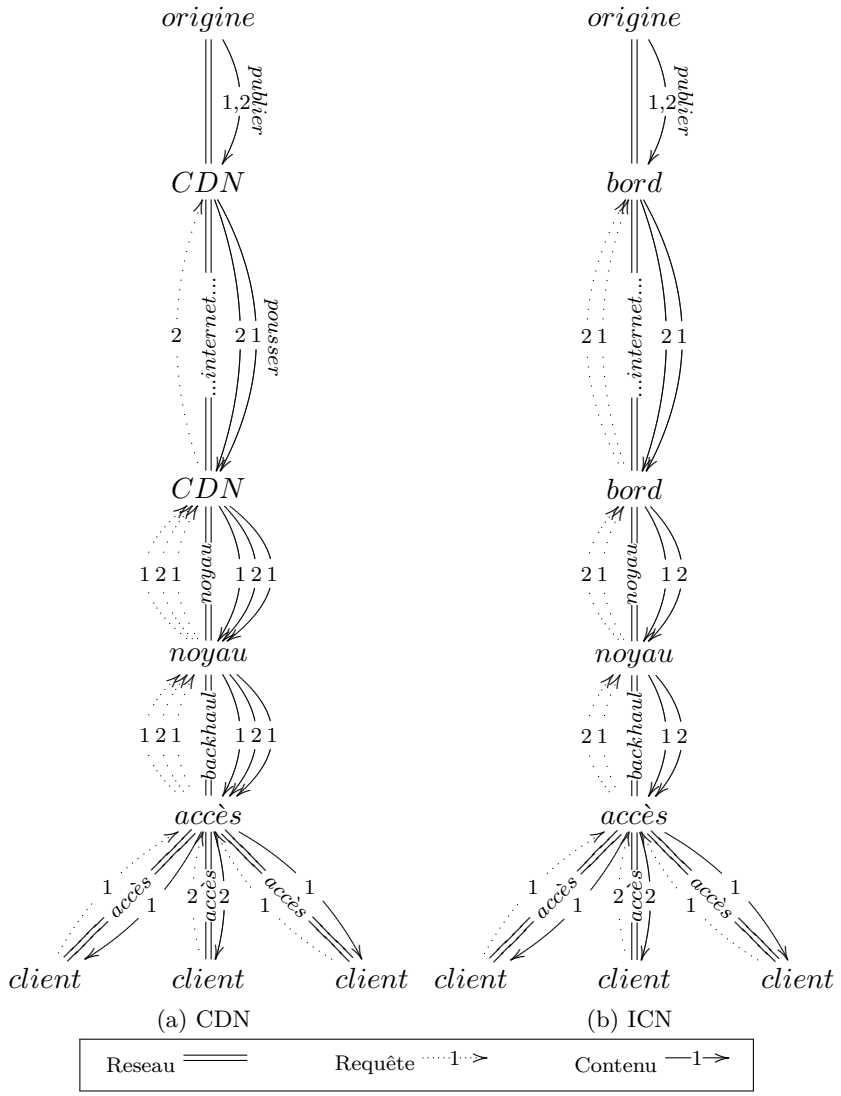


Figure D.1: Modèle de livraison du contenu: CDN vs ICN. Example de livraison d'un object populaire (1) et un objet moins populaire (2).

le logiciel et l'infrastructure d'internet. Les avantages et désadvantages de ce paradigme doivent être étudiés minutieusement, parce que seulement des resultats excellents peuvent resulter en sa adoption. En particulier l'efficacité des caches avec peu d'utilisateurs doit être analysée.

Pour résouder les problèmes entre les ISPs et les fournisseurs de contenu, nous proposon une approche nouvelle, dénommé *micro CDN*[4], qui combine la flexibilité du service tipique de CDNs avec la réduction du trafic redondant. Une microCDN utilise un petit

stockage à haute vitesse. Certaines technologies existent déjà pour atteindre cet objectif, par example JetStream [5], AltoBridge [6] et Open Connect [7]. Toutefois, ils ne fournissent pas d'architecture standardisée, ils n'intéroperont pas, et ils ne supportent pas tout les types de contenu web. Une approche ICN peut, selon nous, atteindre cette objectifs, en particulier en considerant CCN (Content Centric Networking – Reseau Centré sur le Contenu), et NDN (Named Data Networking – Reseau de Contenus Nommés)[8]; en intégrant un système de caches dans l'architecture du reseau, CCN peut fournir un substrat commun pour le déploiement de systèmes CDN de nouvelle géneration.

Alors que les microCDNs sont techniquement faisables, les ISPs n'ont pas d'incentives pour les deployer sans des gains considérables. While micro CDNs are technologically feasible, ISPs would have incentives in deploying them only provided that gains are sizable. À travers de mesures et analyses statistiques, cette thèse montre que cacher dans le reseau d'accès est une vraie opportunité pour les ISPs.

Décider l'emplacement et la taille des caches dans un reseau est fondamental pour maximiser l'efficacité et les gains. D'autre part, cette décisions peuvent être effectuées seulement avec assez d'information sur le requêtes; recueillir cettes informations est extrêmement compliqué à cause de la quantité énorme de donnés qui doivent être gérés pour effectuer cette estimation. Des compromises ne sont pas idéals: par example, l'*echantillonage* des requêtes peut conduire à filtrer du façon excessivement optimiste les contenus moins populaires, et donc à surestimer les gaines du au caching; *limiter* le débit de données maximum limite l'analyse aux bords du reseau où la quantité limité d'utilisateurs peut avoir un impact négatif sur l'estimation, nous conduisant à une sous-estimation des gains du au caching; operer sur des *registres de fluxes* implique perdre des détails importants (par example requêtes d'intervalles, cookies, etc.) necessaires pour l'identification des objets, qui conduit de nouveau à surestimer. Evidemment, combiner une quelconque des simplifications ci-dessus peut conduire à des erreurs d'amplification ou de compensation incontrôlées.

Heureusement, dans les dernières décennies il y a eu un écosystème florissant d'outils logiciels [9, 10, 11, 12, 13, 14] pour gérer des quantités énormes de données; ces systèmes sont étiquettés "megadonnées" ("Big Data" en anglais). Le paradigme "Map-Reduce" (map-réduction) est l'example le plus connu, initiallement proposé par Google[15], dont l'implementation la plus connue est Hadoop[10], créé par Yahoo. Initialement proposé pour l'analyse distribué des registres, le paradigme a été adapté rapidement pour autres buts, y compris l'analyse des reseaux et du trafic [16, 17, 18, 19, 20, 21, 22]. Les raisons pour ce succès sont évidents en considérant que, à condition que le problème à resoudre soit parallélisable, le paradigme Map-Reduce offre un'évolutivité linéaire. C'est-a-dire,

quand un système d'analyse a été développé, il peu être appliqué à des données plus grands en parallélisant le calcul sur assez ressources hardware (par example processeur et mémoire vive). Dans l'âge du déluge de données numeriques, et en raison d'une augmentation attendue du trafic, cette propriété devient obligatoire pour maintenir la faisibilité du calcul.

Par consequence, il vaut la peine d'utiliser un approce megadonnées pour le problème de l'estimation de la cacheabilité du trafic, qui est le but de cette thèse. Dans un de notres travaux précédents, nous avons abordé l'analyse di trafic avec des techniques plus traditionelles. Pourtant, nous avons eu des problèmes significatifs en appliquant la même méthodologie à des données plus massives – plus longues, avec plus de clients et avec une plus grande bande passante. Dans cette thèse nous avons résolu ces problèmes avec le paradigme Map-Reduce.

Les contributions principales de cette thèse sont les suivantes:

— Outil d'analyse du trafic: conception et développement d'un outil d'analyse en temps réél pour dissection et analyse à hautes prestations et à vitesse de ligne. Notamment l'outil peut analyser du trafic HTTP à 10Gbps avec un seul cœur.
— Analyse de l'échelle temporelle: inférer l'échelle temporelle dans laquelle il y a des avantages concrets pour cacher dans le reseau d'accès.
— Analyse de la popularité des contenus: analyser et charactériser la popularité des contenus das une échelle temporelle significative.
— Dimensionement des caches: determiner une bonne taille pour une vraie cache dans le reseau d'accès, et la valider avec des simulations.
— Stratégies d'identification des objets: analyser l'impact de différents strategies d'identification des objets à cacher sur les statistiques de cacheabilité.
— Système Map-Reduce: conception et implementation d'un système d'analyse évolutif en utilisant Hadoop, un système Map-Reduce.
— Analyse comparative du système Map-Reduce: mesurer l'impact sur les prestations de Hadoop de différentes optimisations.

Outil de capture et données collectées

L'analyse de la cacheabilité est evidemment possible seulement si il est possible d'analyser du trafic réel. Les deux conditions préalables sont l'accès à un reseau opérationnel et une sonde pour capturer le trafic et extraire les données en temps-réel pour les analyser plus tard.

Nous avons eu l'opportunité de placer notre sonde dans un Nœud Central du réseau

de Orange à Paris. Le réseau est organisé comme indiqué dans la figure D.2. L'arbre GPON (Gigabit Passive Optical Network – Réseau Passif Optique Gigabit) aggrége jusqu'à 64 utilisateurs dans un seul lien optique, et jusqu'à 16 liens optiques sont ensuite agrégés chez le OLT (Optical Line Terminal – Terminal Optique de Ligne), avec un lien vers le noyeau.

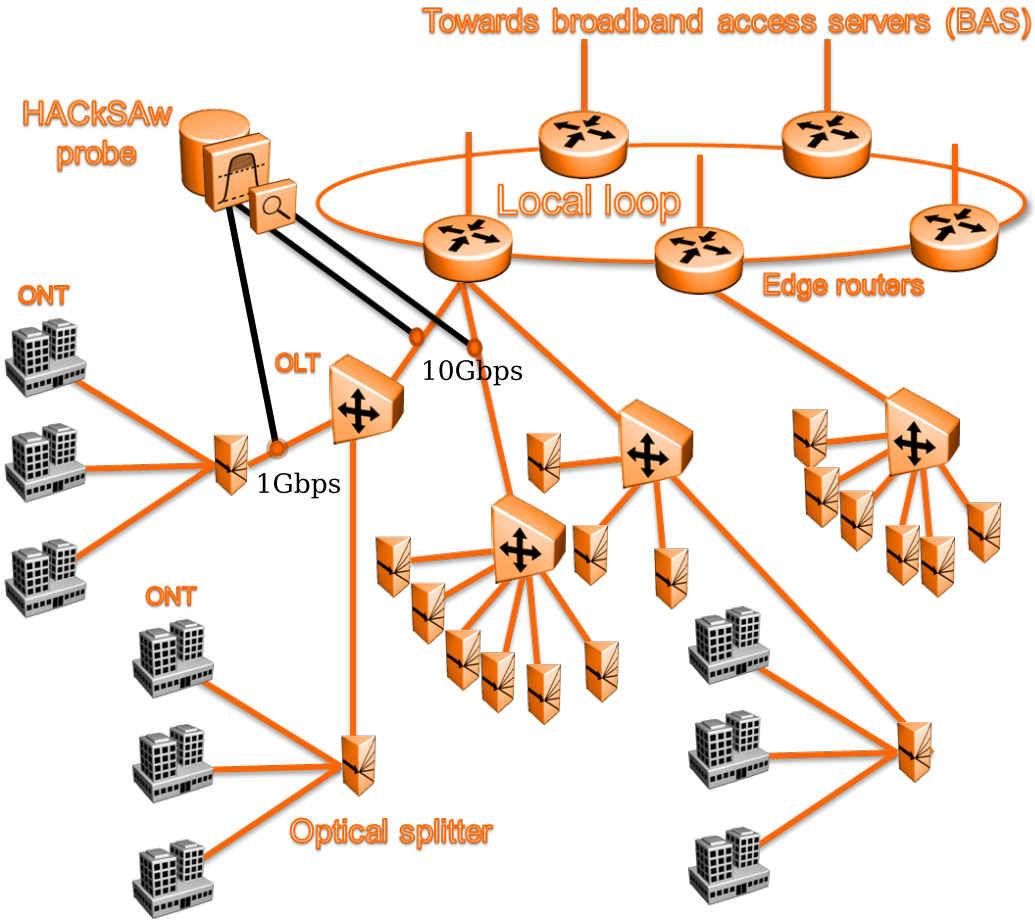


Figure D.2: Accès fibre et lien backhaul dans un réseau d'un ISP. Notre sonde, nommée *HACkSAw*, est déployé dans différentes positions (OLN et OLT), avec des vitesses de ligne différentes (1Gbps et 10Gbps), et niveaus d'agrégation différentes (1 500 et 40 000 clients).

En 2014 nous étions aval de 2 OLTs, chaque avec un lien de backhaul de 1Gbps, et comme prévu nous avons observé moins de 2 000 clients. En 2015 nous avons déplacé la sonde un niveau plus en haut, où la sonde était en amont de 2 liens 10Gbps, et en aval d'un BAS (Broadband remote Access Server). Les liens agrègent plusieurs liens de

backhaul des OLTs, et là nous avons observé plus de 30 000 clients. Dans les deux cas, les paquets capturés étaient encore encapsulés dans PPPoE, et ils avaient des tags VLAN.

Notre sonde est un serveru IBM avec 2 precesseurs quad-cœur Intel Xeon E5-2643 à 3.30GHz, chaque avec 48Go de mémoire vive, pour un total de 96Go; il s'agit donc d'une configuration NUMA (Non Uniform Memory Access – Accès à la Mémoire Non Uniforme). Le serveur a 5 disques durs de 1To, en une configuration RAID-5. Le système d'exploitation utilisé est Debian.

Le servuer est equippé avec une carte Endace DAG 7.5G (DAG 10X4-P pour les données du 2015), qui peut capturer les paquets de 4 liens simultanément, permettant ainsi de contrôler 2 liens Gigabit (10Gigabit pour les données du 2015).

L'analyse du trafic n'est pas certainement une nouvelle technologie, et donc il y a déjà des outils pour le faire; certains outils sont plus adéquats à nos besoins. Les outils qui sont effectivement adéquats, malheureusement, ne sont pas disponibles; par contre, les outils qui sont disponibles, ne sont pas vraiment adéquats à nos besoins, donc il était nécessaire d'écrire un nouveau outil.

Les contraintes pour l'outil sont:

— Analyse en ligne et hors ligne. L'outil doit être utilisable pour analyser du trafic énregistré, mais son objectif est l'analyse en ligne

— API PCAP et DAG. Les APIs DAG sont fondamentalles pour attaindre la vitesse de ligne à haute vitesse, alors que les APIs PCAP sont très répandues, et plusieurs logithèques fournissent des niveaus de compatibilité avec PCAP. En utilisant PCAP, il est possible de supporter toutes logithèques, du present ou du futur, qui fournissent cette strate de compatiblité.

— Consommation de mémoire vive pas trop élévée. Il ne doit pas être necessaire que la sonde ait des quantités de mémoire énormes, pour raisons de côut, efficacité et evolutivité.

— Analyse du HTTP et DNS. Analyses exhaustives des transactions HTTP et DNS, y compris informations du timing, taille des objets, et autres entêtes et informations.

— Facile à maintenir et étendre. Idéalement la conception doit être modulaire, pour permettre d'étendre et de maintenir facilement.

— Analyse à 10Gbps to 40Gbps (ou même à 100Gbps) sans perte de paquets. L'outil devrait être capable d'analyser le trafic dans diffenrents points du reseau à vitesse de ligne, y compris proche du noyeau.

— Distribution correcte du logiciel: script de configuration, makefile, et scripts de démarrage pour exécuter l'outil comme démon.

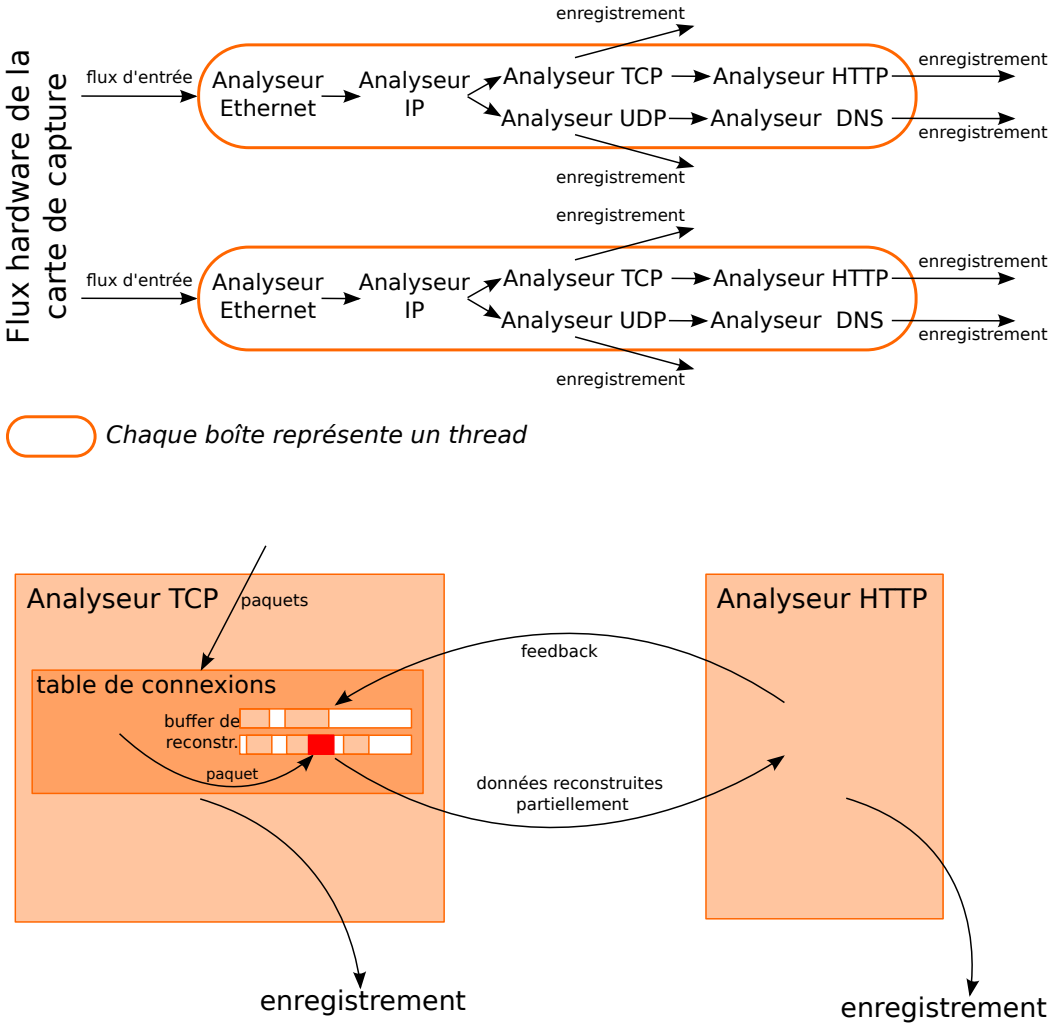


Figure D.3: Schéma fonctionnel du logiciel HACkSAw.

L'outil HACkSAw est écrit entièrement en C pour systèmes Linux à 64 bit. Autres langages de programmation ne sont pas appropriés pour la tâche. L'outil peut être configuré avec des paramètres à ligne de commande ou avec un fichier de configuration.

La sortie du logiciel est constitué de plusieurs fichers de texte brut, un pour chaque protocol analysé. Chaque ligne représente une connexion ou une transaction, avec les valeurs separés par des espaces ou tabulations. Ça n'est pas certainement la manière la plus efficace pour stocker ces informations, mais il était nécessaire d'avoir des resultats faciles à analyser manuellement, et faciles à traiter avec les outils à ligne de commande UNIX, et en outre il était nécessaire de garder en bas la complexité du logiciel même.

La Figure D.3 montre le schéma fonctionnel de l'outil. Les API DAG sont utilisées directement, pour pouvoir utiliser les files hardware fourinies par la carte. Pour chaque paquet, la carte calcule les hachages des adresses et place le paquet directement dans la file correcte en memoire vive. Malheureusement cette solution ne nous convient pas, parce que nos paquets ont encore les entêtes PPPoE.

La structure du logiciel est complètement modulaire. Les modules d'entrée, d'analyse et de sortie sont configurables. L'organisation interne modulaire du logiciel permet d'ajouter des nouveaus modules très facilement, et sans un gros impact sur le reste. Tous les niveaux supportés (L3 à L7) sont aussi modulaires, avec une API interne pour détecter le protocol suivante, pour instantier l'analyseur correct.

Pour maximiser l'efficacité et minimiser le gaspillage de memoire vive, les analyseurs des niveaux 4 et 7 interagissent. L'interaction permet à l'analyseur de niveau 7 d'analyser le flux de données, ou de démander plus de données au niveau 4. Le niveau plus en bas doit donc consever les donnée jusq'au moment quand le niveau dessus en a besoin.

Normalement il y a un seul module de sortie, le module texte-brut. Evidemment il est possible d'implementer facilement des autres modules (par example binaire, base de données, hadoop) selon le besoin. Le module texte-brut divise la sortie en plusieurs fichiers, un pour chaque créneau, dont la durée est configurable. Ça permet, entre autres, de comprimer séparément le fichiers, et de les envoyer tout de suite.

Il y a beaucoup d'allocations de mémoire dans les threads des analyseurs, et ça met beaucoup de pression sur l'allocateur de memoire. Alors que l'allocateur classique ait des bonnes prestations en général, il est possible de faire mieux. Pour ce but un allocateur personnalisé à été implementé, selon le paradigme *slab*.

Le resultat final est que avec l'allocateur personnalisé, il y a une amelioration des prestations de 10% et une réduction de 10% de consomation de memoire.

Une compairason des prestations de differents outils est dans Tab.D.1; la comparaison a été effectué avec le même fichier de capture PCAP d'une heure. Les colonnes de la tabler indiquent, respectivement: nombre de requêtes HTTP distinctes; temps CPU total, cumulé sur tous threads; la quantité de mémoire vive utilisée; le nombre de requêtes détectées sans taille; le nombre de requêtes détectées avec taille.

HACkSAw version 0.2 était la premiere version du logiciel, la version 0.4 est la plus récente. On peut voir que HACkSAw peut détecter un grand nombre de transactions pertinentes, sans utiliser des quantités de mémoire énormes, et avec une consommation de CPU très faible. Dans notre deuxième location, HACkSAw peut analyser 2 liens 10Gbps en utilisant seulement 2 cœurs des 8 disponibles. Nous estimons que avec notre hardware nous pouvons analyser jusq'au 4 ou même 8 liens 10Gpbs.

Table D.1: Comparaison de Bro, Tstat et HACkSAw. Les meilleurs valeurs pour chaque colonne sont en gras.

Outil	**Requêtes détectées**	**CPU [sec]**	**RAM [GB]**	**Réponses sans taille**	**Réponses pertinentes**
Tstat	2 531 210	445	**0.3**	1 128 109	1 403 101
bro	**2 559 056**	8033	4.2	424 355	**2 134 701**
HACkSAw 0.2	2 426 391	368	5.8	328 465	2 097 926
HACkSAw 0.4	2 393 514	**235**	**0.3**	**269 311**	2 124 203

Chaque transaction HTTP est enregistré avec des statistiques: temps, ID utilisateur, ID objet, `Content-Length`, longueur réelle, et informations sur les intervals des requêtes HTTP de type `Range`.

Dans le premier dataset nous avons observé que 15% du trafic Web était crypté, dans le deuxième 30% était crypté, et ces nombres vont augmenter grâce à l'introduction de HTTP 2.0.

Nous avons collecté trois ensembes de données: le premier (`2014`), 42 jours, du 18 avril au 30 May 2014; le deuxième (`2015-1`), 30 jours, su 10 janvier au 9 février 2015; le troisième (`2015-6`), 132 jours en total: su 11 juin au 23 novembre 2015, avec deux interruptions. Le tableau D.2 montre un resumé des ensembles de données collectés pendant cette thèse et dans autres œuvres.

Table D.2: Comparaison des ensebles de données collecté dans cette et dans autres œuvres. Les plus grandes valeurs dans chaque colonne sont en gras.

Référence	**Durée**	**Clients**	**Requêtes**	**Objets HTTP**	**Trafic HTTP**	**Économies requêtes**	**Économies trafic**
`2015-6`	**132 jours**	40k	**26.3G**	**8.9G**	**3.2Po**	52%	31%
moyenne quotidienne		*22k*	*194M*	*90.9M*	*23To*		
`2015-1`[?]	30 jours	30k	6.6G	2.5G	575To	53%	40%
moyenne quotidienne		*24.5k*	*220M*	*102M*	*19To*		
`2014`[4]	42 jours	1.5k	369M	174M	37To	42%	35%
moyenne quotidienne		*1.2k*	*8.6M*	*5M*	*881Go*		
[48]	14 jours	20k	–	–	40To	16–71%	9.5–28%
[49]	14 jours	20k	–	–	42To	–	–
[50]	1 jour	200k	48M	7M	0.7To	10–20%	13–40%
[32]	8 jours	**1.8M**	7.7G	–	248To	54%	41%
[31]	1 jour		42M	–	12To	16%	7%
[24]	1 jour	–	6M	–	–	–	–

Le Tableau D.2 montre une comparaison de notres ensembles de données avec les ensembles de données les plus éminents utilisés dans la literature. Les plus grandes valeurs dans chaque colinne sont en gras; les plus grandes valeurs dans chaque colonne sont en gras.

Nos ensembles de données sont les plus longues; notamment le troisième couvre plus que 4 mois. Simplement en considerant le volume du trafic, on peut voir que nos ensembles des données sont les plus grands; notamment le troisième, avec $3.2Po$ du trafic total, est plus grand que tous les autres combinés.

Il est important de remarquer que notres statistiques sont cohérent avec eux-mêmes et avec celles utilisées dans la littérature.

Cacheabilité

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