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A 6-month Analysis of Factors Impacting Web Browsing Quality for QoE Prediction

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ABSTRACT

Web browsing is one of the main Internet services, which has largely evolved over the last years. It now includes many different components (images in various formats, css, Javascript, Progressive Web Apps, etc.) and a web page is composed of many different resources provided by many servers located in various places. Knowing how web browsing content is delivered is crucial for better understanding the Quality of Experience (QoE) offered to end-users. Detecting the factors impacting this QoE is important to improve them but also to be able to predict the quality in order to anticipate degradations to it and propose remediations, which is the main goal of our study. For this, we present an analysis of a measurement campaign we have performed during 6 months (July 2018 - January 2019) on the Top 10,000 Alexa websites, which helps to identify the main factors which can impact the quality perceived by end-users. This set of factors has been confirmed by a machine learning process (decision tree), which gives as outputs the set of rules to predict the QoE. The evaluation of our decision tree-based model, on the Top 10,000-15,000 Alexa websites, never accessed before, shows that we can correctly predict the web browsing quality an end-user can get.

1. Introduction

Web browsing is a fast-paced and changing domain and needs to deliver a good experience to end-users since a plethora of applications and services are nowadays accessed through web browsers. The Web was originally designed to deliver static contents but has evolved dramatically towards dynamic web pages offering to end-users a built-in environment for education, gaming, video streaming or social networking [1, 2, 3]. Large service companies (e.g Google, Mozilla, Apple, etc.) are following the trend of new technologies by enabling Virtual Reality, Virtual Machines or IoT (Internet of Things) applications embedded in the web browsers. They are delivered over HTTP/1.1 but also over new transport protocols such as HTTP/2 (Version 2 of the HyperText Transfer Protocol) [4], standardized in 2015, or QUIC (Quick UDP Internet Connection) [5, 6] which is paving its way to standardization, as HTTP/3. Network operators or service providers need to offer the best possible QoS (Quality of Service) to their customers and for this, they deploy Content Delivery Networks (CDN) and proxy-based networking architectures, aiming to improve the web browsing delivery.

The question of measuring the quality when performing web browsing and the need to identify the main factors decreasing or enhancing it is then of prime importance. Measuring web browsing quality needs to be performed in a meticulous manner by taking into account the latest rich-exposed browsers' functionalities. Based on a large measurement campaign we performed over 6 months (July 2018 - January 2019), our first contribution provides an overview of today's web browsing delivery, including the number of resources, their location, the protocol used, etc. Secondly, we perform a detailed study of these parameters' impact on end-users' perceived quality, in order to highlight the factors which are the most critical for Web browsing. Thirdly, we

use Machine Learning techniques to validate the identified factors and through a decision tree model, we identify the thresholds of these factors in order to automatically predict the end-users web browsing quality. Then, the identified set of rules of our model are applied on the Alexa top 10K-15K websites and our model proves to be efficient, predicting correctly more than 90% of measurements.

The paper is structured as follows: We first remind in section 2 the existing web metrics and related work meant to quantify and qualify web browsing. Through section 3 we introduce how our measurement campaign is performed, section 4 depicts how web browsing content is delivered to end-users and section 5 analyses the impacts of the parameters on web browsing quality. Section 6 presents our rules-based model to predict web browsing quality. We finally conclude in section 7.

2. Background and Related Work

Policies and processing algorithms used by web browsers to render web pages are all different. In order to bring uniform benchmarking indicators, standardization bodies such as the W3C, in collaboration with large service companies, have defined a set of web metrics to measure web page loading better. The Page Load Time¹ (PLT) is the time between the start of the request and when the entire web page has been loaded. The Resource Timing² provides information upon the downloaded resources unit-wise, such as the transport protocol used, size and type of object or some low level networking information. The Paint Timing³ exposes the First Paint (FP) which is the time for a first pixel to appear on the end-user's web browser screen. The Above-The-Fold (ATF)

¹<https://www.w3.org/TR/navigation-timing/>

²<https://www.w3.org/TR/resource-timing-2/>

³<https://www.w3.org/TR/paint-timing/>

[7] exposes the time needed to fully load the visible surface area of a web page at first glance (making use of W3C information). The TFVR (Time for Full Visual Rendering) [8] exposes the loading time of the visible portion of a website at first glance (without scrolling) by making use of networking information through the web browser's exposed HAR (HTTP Archive). The Speed Index and RUM (Real User Monitoring) expose a score representing the visible surface area occupancy of a web page. The Latency Amplification Factor (LAF) [9] characterizes the content of a web page in terms of how it affects the page load time.

When end-users go to a website, *third parties* such as advertisement networks can impact web browsing quality [10, 11, 12]. To measure QoE during web browsing sessions, several tools have been developed by the research community. *FPDetective* [13] uses a PhantomJS⁴ and Chromium based automation infrastructure, *OpenWPM* [14] performs automated web browsing driven by Selenium⁵ while supporting stateful and stateless measurements and the *Chameleon Crawler*⁶ is a Chromium based crawler used for detecting browser fingerprinting. *Fourth Party* [15] instruments the Mozilla-Firefox browser and *Web Xray* [16] is a PhantomJS based tool for measuring HTTP traffic. *XRay* [17] and *Ad-Fisher* [18] run automated personalization detection experiments and *Common Crawl*⁷ uses an Apache Nutch based crawler. Kaleidoscope [19] is an automated tool to evaluate web features on a large scale focused on the web page style and page loading times. All these tools (among others) have largely contributed to the research field but when wanting to objectively quantify and qualify web browsing, there is a clear need to finely reproduce an end-user environment and usual interaction with the latest web browser functionalities, which they do not offer. We have thus developed our own tool highlighted in section 3 which offers fine-grained information through the latest implemented web metrics and data obtained from network capture and browser's offered HTTP Archive (HAR). We also collect information regarding the different remote web servers located all over the world, the downloaded resources' type, size and Internet protocol through which they are delivered at different stages of the web page loading process.

Web browsing includes 4 key actors, namely the end-user, the web browser, the network and the remote web server. While some research work [20, 21] describes how to qualify user-experience better, other studies investigate the impact of different Internet protocols on web browsing quality [22, 23, 24, 25, 26, 27]. Regarding the network, particular interest is given to the upload or download link when investigating bottlenecks [28, 29, 30] and Naseer and al. [31] propose a tool in order to analyze and better understand the actual configuration parameters employed by today's web servers. The PLT is the de facto used web metric but with the evolution of websites' characteristics, researchers ques-

tion the versatility and objectiveness of this metric to measure end-user's QoE [32, 33, 34, 35, 36] emphasizing that what the user really sees on the screen should be primarily measured. Other research work proposes ATF browser-based measuring techniques [37, 8] in order to measure the websites' visible portion loading time. When studying web browsing performance as a whole, different on-market web browsers, Internet protocols, network bandwidths and types of websites need to be taken into account. We have thus focused our research work by taking into account the mostly used on-market web browsers, studied the impact of different Internet protocols (HTTP/1.1, HTTP/2 or QUIC), used different types of residential network access (ADSL, Wi-Fi, Fiber) and assessed the Top 10,000 Alexa websites. Our measurements include all the web metrics defined by the W3C and the TFVR (Time for Full Visible Rendering) [8].

3. Measurement Campaign Setup

Our measurement campaign has been performed with the tool Web View[38]. Web View is a measurement platform whose infrastructure includes probes and a public visualization website⁸ illustrating the obtained measurement results for a set of websites. The Web View probe is a user-orientated measurement tool whose main objective is to perform automated web browsing sessions and measure representative information of web pages in order to better qualify and understand web browsing, both in terms of quality and delivery. Each test can be configured with several parameters, such as the web browser, the access network type on which the probe is connected, the list of websites to measure, the preferred transport protocol to get the contents (HTTP/1.1, HTTP/2, QUIC), etc.

For this study, we deployed probes in France, three different desktop machines (CPU Intel Core i5 and 8 GB RAM) connected to three different user-representative residential network accesses, i.e ADSL (10Mbps down, 1Mbps up), Wi-Fi (200Mbps down, 160Mbps up) and FTTH Fiber (800Mbps down, 300Mbps up). The Wi-Fi network access (802.11 b/g/n, 2.4Ghz and 450Mbit/s max) is provided by a homebox, connected to the Fiber operational network. Our probes are located in the same room as the Wi-Fi homebox. Two popular web browsers, with different window sizes, were used, namely Google-Chrome (version 63 and 68) and Mozilla-Firefox (version 56 and 62). The Google-Chrome browser is driven by Chromedriver v.2.36 and v.2.40 and Mozilla-Firefox by Geckodriver v.0.19 where the main automater is Selenium v.3.14. Both browsers support HTTP/1.1 and HTTP/2, but only Google-Chrome implements QUIC. The automated web browsing sessions were conducted at different times of the day by requesting different Internet protocols. Some Internet protocols might be disabled or blocked by service providers or corporate companies and the need to study what the obtained quality is when an Internet protocol is not available is important. When requesting HTTP/1.1, we deactivate the HTTP/2 and QUIC protocols in the browser; when request-

⁴<http://phantomjs.org/>

⁵<https://www.seleniumhq.org/>

⁶<https://github.com/ghostwords/chameleon>

⁷<https://commoncrawl.org/>

⁸<https://webview.orange.com>

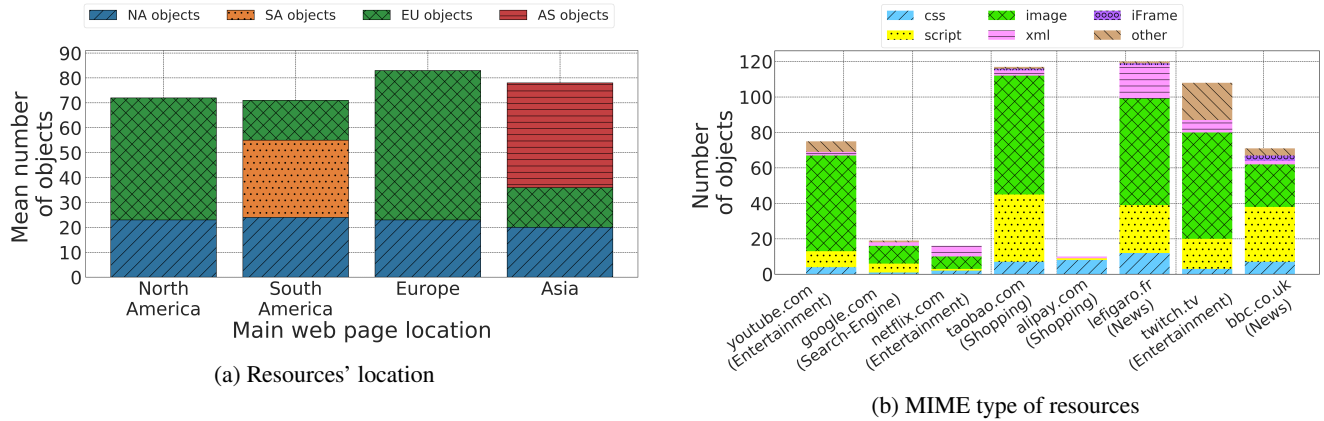


Figure 1: Downloaded resources

ing HTTP/2 we deactivate QUIC but allow fallback to HTTP/1.1 (not all content-servers are HTTP/2-enabled); when requesting QUIC, we allow fallback to HTTP/1.1 and HTTP/2 for non-UDP web servers. We also define another mode, the QUIC Repeat. This mode favors 0-RTT UDP and 1-RTT TCP by firstly performing a navigation to the website, closing the browser, clearing the resources' cache but keeping the DNS (Domain Name System) cache and going once more to the website when we collect measurements. For all our measurements, the resources' cache is always emptied at the start and end of web browsing session, and we have defined a timeout of 18 seconds (this value has been set since it is a very long time to wait for a web page and after more than 18 sec, all end-users will have given up the browsing). For every visited website, Web View probes measure and compute 84 parameters⁹. Amongst them, we have 4 different loading times, namely the First Paint (FP), Time for Full Visual Rendering (TFVR), the processing time (DOM time) and the Page Load Time (PLT). We also collect network traffic from which we investigate the corresponding DNS time for the main web page domain and through the collected HAR¹⁰ we assess the overall number of objects downloaded and their MIME (Multipurpose Internet Main Extensions) type. From the exposed remote servers' IP address correlated to MaxMind GeoIP2 database¹¹ and RIPE NCC database¹², we estimate the continents from which these resources are downloaded. Web View also identifies if the resources are delivered with secure connections or not, the number of domains serving the contents and the category of the website as referenced by Alexa. As per the different collected timings, which indicate a web page page loading progression through time, we also collect the number of resources downloaded in these periods of time as well as the Internet protocol through which they are delivered.

After our 6-months campaign on the top 10,000 Alexa

⁹<https://webview.orange.com/monitoringParameters>

¹⁰HTTP Archive

¹¹<http://www.maxmind.com>

¹²<https://stat.ripe.net/>

websites, we got 244 Million different measurements, representing the measurement of 9597 distinct websites. 403 distinct websites were discarded due to the small amount of web browsing results (these websites were either unavailable, blocked as per our geographic location or not responding in less than 18 seconds). Our dataset then includes measurements for websites having their main web page estimated to be in North America (NA) for 52.23%, in Europe (EU) for 28.44%, in Asia (AS) for 16.22%, and in South America (SA) for 1.10%.

4. Web Browsing Delivery Analysis

We present in this section an analysis of our collected measurements and highlight the main evolutions of web browsing delivery with regards to previous studies [39, 9] which have identified that the category of a website (as per Alexa ranking), number of objects embedded in the web page and amount of web servers delivering content has an impact on web browsing quality. A part of our dataset is made public at <https://webview.orange.com/public/dataset.zip>.

4.1. What are these objects ?

The web pages are more complex nowadays and we wanted to evaluate their evolution, compared to what it was few years ago [39, 40, 41]. When a main web page is located in Europe, on average between 2 and 47 resources need to be downloaded for less than 25% of the websites and between 125 and 230 resources need to be downloaded for more than 75% of these websites. Since 2014, the amount of downloaded resources composing a web page has increased by 17% on average for the Alexa websites ranked 1-2000 and by 31% on average for websites ranked 5000-10000.

Going deeper into the question from where the resources are downloaded, (Fig.1a) presents the location of the servers. On average, when a main web page is located in North America, a mean number of 72 resources is downloaded, mainly from EU and from NA. When a main web page is in Asia, an average number of 78 resources is downloaded, about half

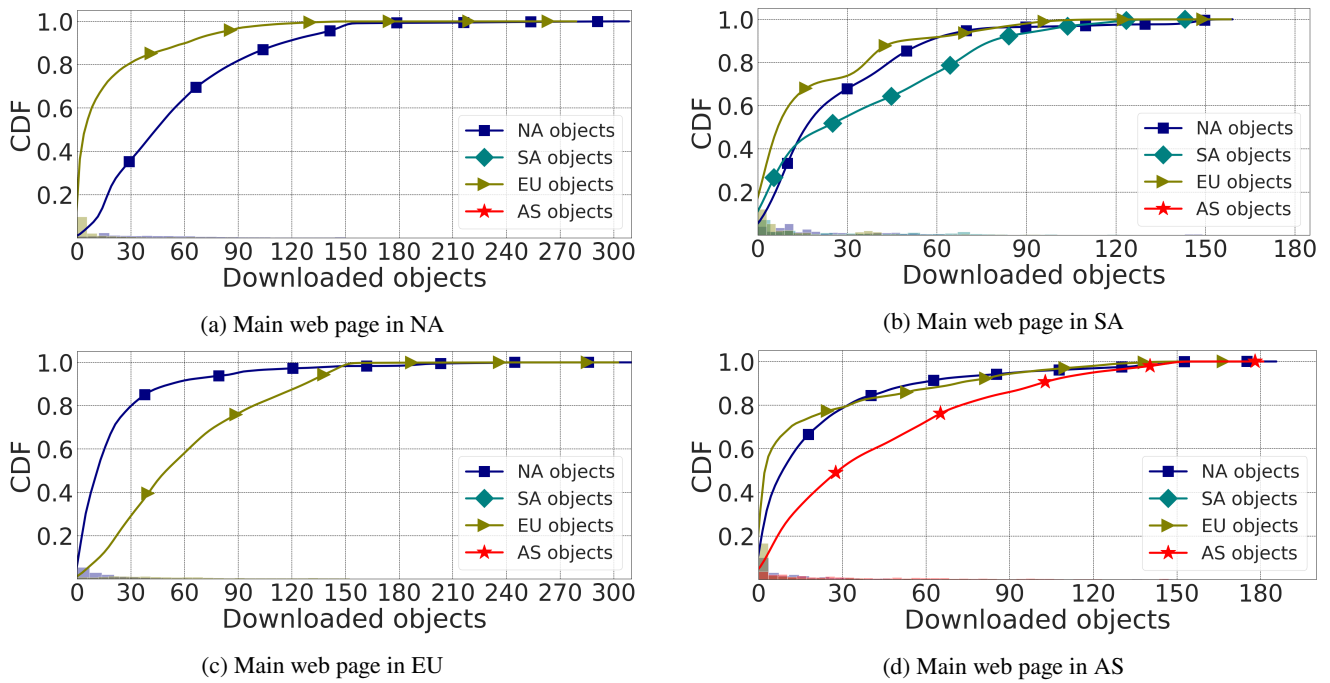


Figure 2: Aggregated distribution of resources

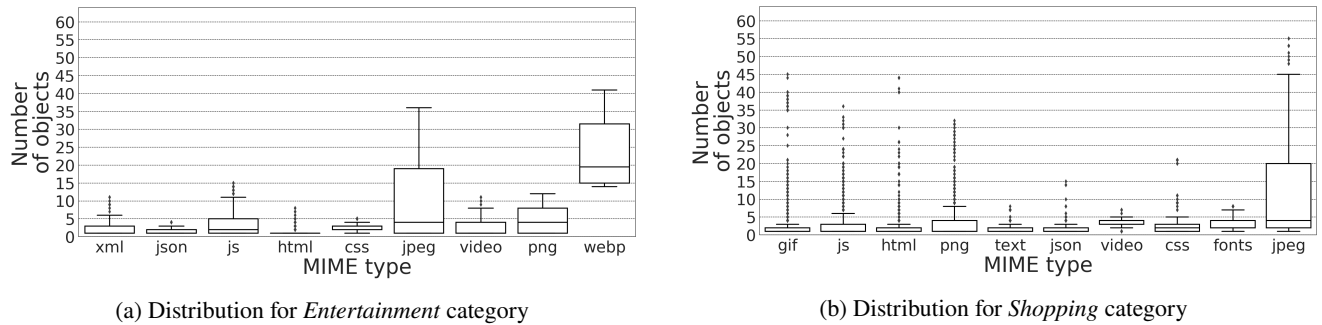


Figure 3: MIME types of objects per category

from Asia, and the other half from NA and EU. The mean distributions help in profiling the overall location of the content servers for a European end-user. The Fig.2 provides the complete distribution of downloaded resources for the 4 continents where the main home page is. The Fig.2a shows that when a main web page is located in North America, for 50% of the measurements, more than 8 objects are downloaded from EU and 50 objects from NA. On the other hand, the Fig.2d shows that when a main web page is in Asia, for 75% of the different measurements, up to 65 objects are downloaded from AS, 20 objects from EU and 27 objects from NA. We can observe that for a European end-user, many objects are downloaded from Europe, which is due to Content Delivery Networks. For main web pages located in Asia, we can detect that many resources are coming from Asia, which could impact the quality, because of the network delay.

Following the question about what these objects are, Fig. 1b represents the breakdown of the downloaded objects by

content MIME types of 8 random websites belonging to different categories as referenced by Alexa. While images occupy most of the time the highest distribution type of resources, on average web pages (except *Search-Engines* category) are composed of 4 css, 5 scripts, 16 images and 2 xml. We identified that the average number of scripts and images has increased by 53% over the last 15 years from past studies [42] and by 7% from recent studies [39]. Furthermore when paying particular attention to the different types of images, when using a Google-Chrome web browser and visiting a Google website, on average 80% of images are now in WebP format. Compared to studies conducted in 2011 – 2014, Flash usage has been reduced by 61% as Adobe will remove all support for Flash in 2020. When performing our measurements, we also noticed an increasing PWA (Progressive Web Apps) usage of 6% between July 2018 and January 2019. On a wider scope, based on the Alexa websites Category listings available, 3921 websites were assessed. The *News* websites download on average 19.81% more resources,

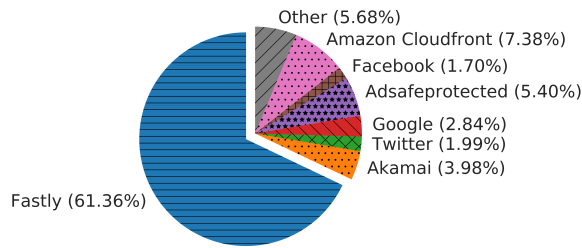


Figure 4: Website *lemonde.fr* content servers

Kids and Teens websites have a significant greater fraction of Flash objects and *Shopping* websites make greater usage of JavaScript. When assessing the overall distribution of resources aggregated by MIME type, the Fig. 3 represents two different Alexa-referenced categories where a large variety of objects are incorporated in the corresponding web pages. We selected these 2 categories, since they represent a major part of the popular websites. The Fig. 3a shows that *Entertainment* websites make greater usage of images (in *WebP*, *PNG* or *JPG* format), followed by JavaScripts and Videos (which can be further decomposed in different formats, e.g *WebM*, *Mp4* or *Mp2t*). The *Shopping* websites (Fig. 3b) also make use of a high number of images in different formats which greatly change all along the day thanks to JavaScript.

4.2. Who is delivering the resources?

In this analysis, we aimed to identify to which extent, when an end-user navigates to a specific website from a given location, the resources needed are downloaded from many servers located at various places. For this, we analyzed if the contents are downloaded from the same authoritative DNS name server of the main web page. Domains delivering contents and having the same authoritative DNS name server as the main web page are entitled *Same-Origin* domains and conversely *Non-Origin* domains. From our global measurements, when a main web page domain is in North America or Europe, irrespective of the preferred Internet protocol, contents are served on average by 2 *Same-Origin* domains and 7 *Non-Origin* domains and when the main web page is in Asia or South America, contents are delivered on average by 3 *Same-Origin* domains and 13 *Non-Origin* domains. Those *Non-Origin* domains represent specific services involved in the web page composition (e.g., Google services, such as advertisements or analytics) but also CDN nodes providing contents on behalf of the origin servers.

The average number of domains is not huge, but we can have some websites with many different domains involved in the delivery. As an example of such a complex website, Fig.4 points out the servers delivering contents when browsing the website *lemonde.fr*, where the main web page is located in Europe and belongs to the *News* category. For this website, 352 resources are downloaded from 29 different domains, where 15 domains located in North America deliver 50 resources and 14 domains in Europe deliver 302 resources. The main web page as well as the 13 *Same-Origin* domains are hosted in Europe by Fastly serving 61.36% of

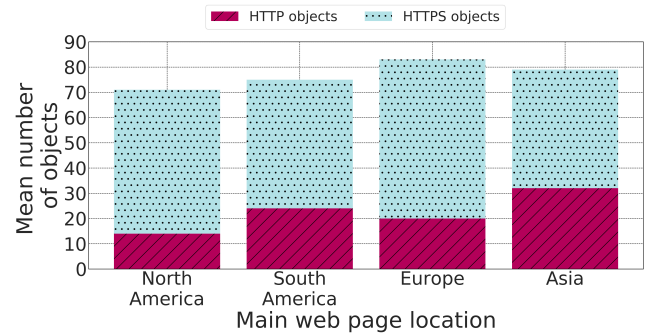


Figure 5: Objects downloaded in HTTP or HTTPS

the overall number of resources, while Akamai and Amazon serve 11.36% of the resources. The *Other* content servers regroup 9 different *Non-Origin* domain web servers. Our website WebView¹³ proposes a graphical representation of this kind of analysis.

4.3. Do websites secure connections ?

Compared to the previous studies [43, 44, 45] encryption has been largely adopted to preserve privacy. Indeed, web browsers nowadays favor it by adding by default *https://* when a user requests a web page. Furthermore, since Google marked non-HTTPS websites as insecure in its Chrome browser in July 2018, HTTPS adoption has increased. However, from our Top 10,000 Alexa websites, only 36.02% of the websites deliver their contents in full HTTPS (100% HTTPS) and still 0.28% of the websites deliver their contents in full HTTP (100% HTTP, no resource composing the web page is delivered by an HTTPS server). In between, we have websites composed of resources received with HTTPS and HTTP. As per Fig.5, on average, when the web page is located in North America, 12 resources are downloaded in HTTP and 70 resources in HTTPS and when the main web page is in Asia, 32 resources are downloaded in HTTP and 46 resources in HTTPS. While HTTP/2 and QUIC-enabled web servers mainly deliver contents in HTTPS through TLS 1.2¹⁴, some content servers still deliver resources in a non-secure mode (HTTP). Those websites are mainly located in Asia.

4.4. Which Internet protocol do I receive?

Since the previous published papers analysing Web browsing, the new Internet Protocols, namely HTTP/2 and QUIC, have been promoted. We then wanted to evaluate the adoption of these protocols by web servers. We made measurements explicitly requesting these protocols and analyzed if the remote servers reply using them or if they fall back to another one. Fig. 6 and Fig. 7 show the results of those measurements, in terms of protocol distribution.

First and very logically, we note that when requesting

¹³<https://webview.orange.com/d/UyIIcrUmz>

¹⁴Now TLS 1.3 is deployed but at the time of the measurements, it was still TLS 1.2

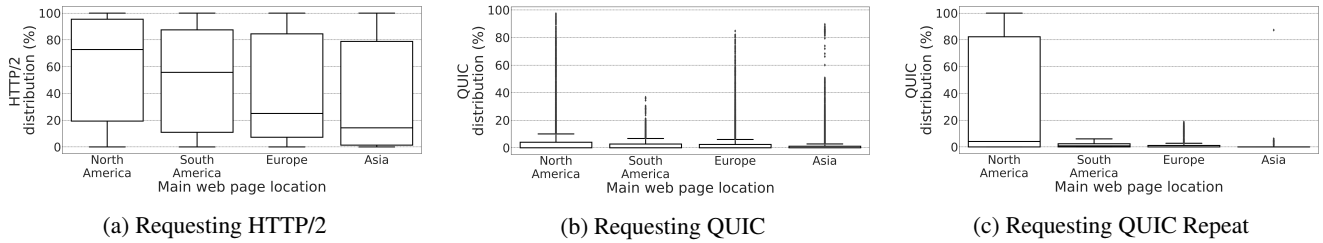


Figure 6: Received protocol distribution upon request

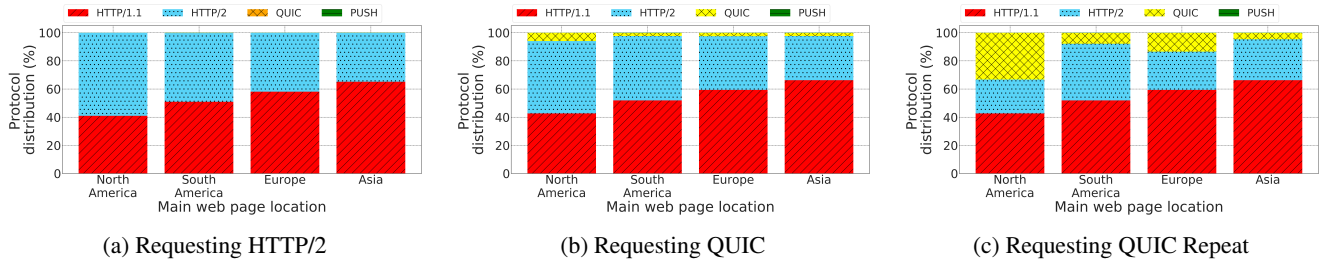


Figure 7: Average received protocol distribution

web pages with HTTP/1.1, all the servers reply with HTTP/1.1. When performing measurements requesting HTTP/2, we received all the resources in HTTP/2 (100% H2) only for 11.82% of the websites. The other 88.18% of the websites reply in an average protocol distribution of 52.04% HTTP/1.1, 46.75% HTTP/2 and 1.21% Server Push. We can then see that although standardized in 2015, HTTP/2 is not yet widely deployed and that it is not equivalent worldwide, more used for servers in NA or SA, whereas in Europe and Asia, HTTP/1.1 is still prevalent.

When performing tests requesting QUIC, we see that QUIC is not deployed by many servers, but mainly Google ones. On average 97% of the different QUIC-enabled web servers are Google servers replying in QUIC v.43 when using Google-Chrome v.68¹⁵ and the other 3% are non-Google web servers replying in QUIC v.37-38 when using Google-Chrome v.63¹⁶. From our measurements, we analyze that 0% of the websites reply in full QUIC for all the resources (100% HQ) and that the responses are received at an average distribution of 6.12% QUIC, 50.57% HTTP/2, 42.1% HTTP/1.1 and 1.21% Server Push. QUIC responses are highest when the main web page is in North America (in particular from Google servers).

QUIC is natively used jointly with HTTP/2 for the first request, but offers a QUIC zero-RTT connection when connecting to an already known website. We then evaluate if the distribution is different with the QUIC Repeat mode. In this configuration, 7.21% of the websites fully reply in QUIC (100% HQ). The rest of websites, 92.79%, reply in a distribu-

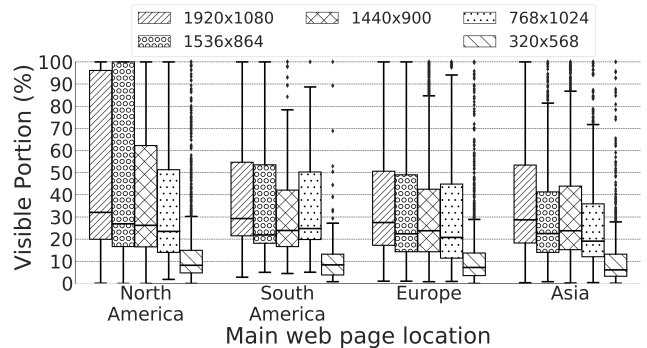


Figure 8: Visible portion of website

tion of 12.71% QUIC, 45.11% HTTP/2, 41.09% HTTP/1.1 and 1.09% Server Push. We can then see that QUIC Repeat favors QUIC reply distribution, because the browser knows that the website can reply in QUIC.

To sum up this evaluation, HTTP/1.1 is still widely used by web servers, HTTP/2, although standardized in 2015, is deployed at a low pace, and QUIC is mainly used by Google web servers.

5. Factors impacting Web Browsing Quality

An indicator of end-users' perceived quality when performing web browsing is the time needed to load a web page (entirely or certain parts of it). This section points out the different factors impacting (decreasing or increasing) these loading times.

¹⁵android.com (90.6% HQ), google.com (52.6% HQ) or youtube.com (49.1% HQ)

¹⁶facenama.com (81% HQ), sarkariexam.com (57.4% HQ) or digital-grant.ru (55% HQ)

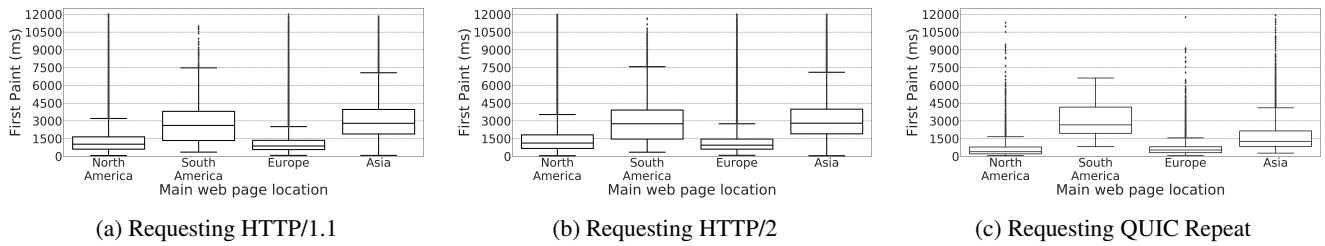


Figure 9: First Paint loading time

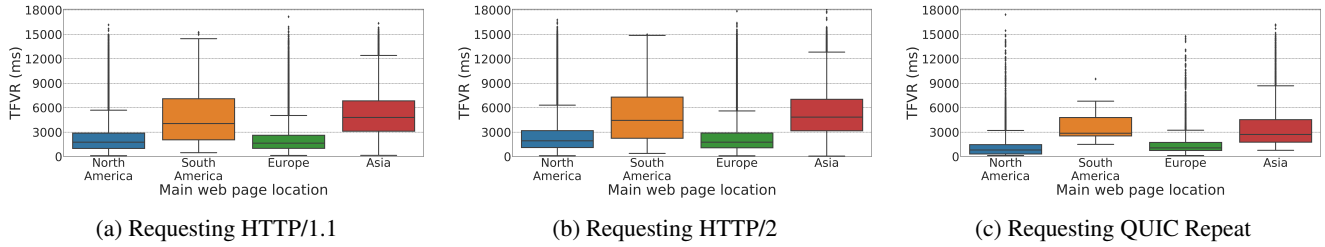


Figure 10: TFVR loading time

5.1. Impact of the requested protocol

We present in this section the impact of the Internet Protocol on the end-users' quality, measured either by the FP, TFVR or PLT. The TFVR provides the loading time of the visible portion of the web page and is tightly linked to the end-user's browser window size. Fig. 8 depicts the different visible portion of web sites (without scrolling the web page) upon different browser window sizes. For example, when the main web page is located in North America, with browser window size of 1920×1080 , less than 50% of the measurements provide a visible portion less than 32.09%. The Page Load Time provides to an end-user the needed time to load the entire web page (visible and non visible parts).

The FP exposes the moment when a first pixel appears on an end-user's browser screen. The FP involves the download and rendering of the main web page *html* source code and on average involves the download of 2 objects from 1 domain for 99.98% of all measurements. The only difference among the measurements is in general the size of the *html* page itself, thus increasing the corresponding download time.

As shown in Fig.9a, we can see that the FP value is very close for HTTP/1.1, HTTP/2 and QUIC. This can be explained since before FP, on average only 2 objects are downloaded in this time and all the benefits of the HTTP/2 protocol (multiplexing, header compression, server push func-

tion) can not happen. Similarly, for QUIC, since the first request is sent using HTTP/2 and the number of objects very small, 99.76% of QUIC measurements receive HTTP/2 replies. But one can see that the FP is smaller for the QUIC Repeat mode, since in this case, resources are downloaded in 0-RTT from UDP-enabled web servers and in 1-RTT from TCP-enabled web servers. The First Paint value is a good indicator of the network state when performing web browsing since objects are mostly downloaded from the main web page domain itself thus decreasing the total DNS time.

Looking at Fig.10 and Fig.11, we can see that the behavior for the TFVR and PLT is close to the one detected with the FP measurement, i.e.; there is no noticeable difference between HTTP/1.1, HTTP/2 and QUIC. Indeed, as depicted in Fig.7, when requesting HTTP/2, the HTTP/1.1 Internet protocol is still largely used. Similarly, with our dataset, when requesting QUIC, about 50% of the measurements have a QUIC distribution less than 0.79%, and those websites fall back to HTTP/2. But for the QUIC Repeat mode, the TFVR is largely smaller, thanks to 0-RTT UDP and 1-RTT TCP. For example, when comparing QUIC Repeat versus HTTP/2, the TFVR loading time is reduced by 54.2% for a main web page in North America.

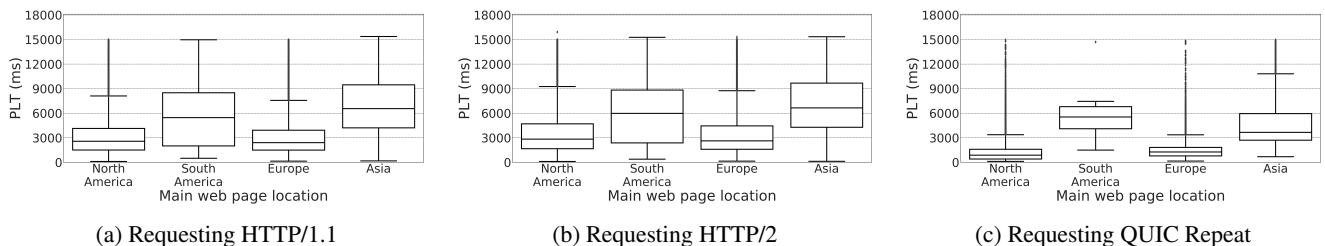
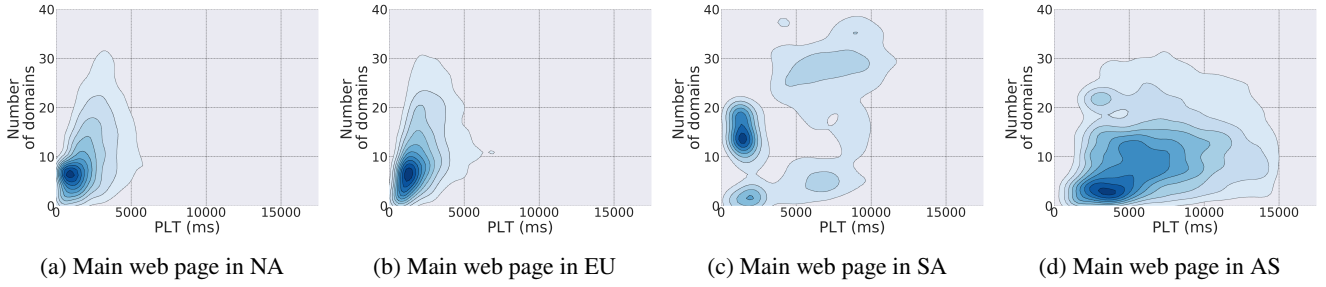
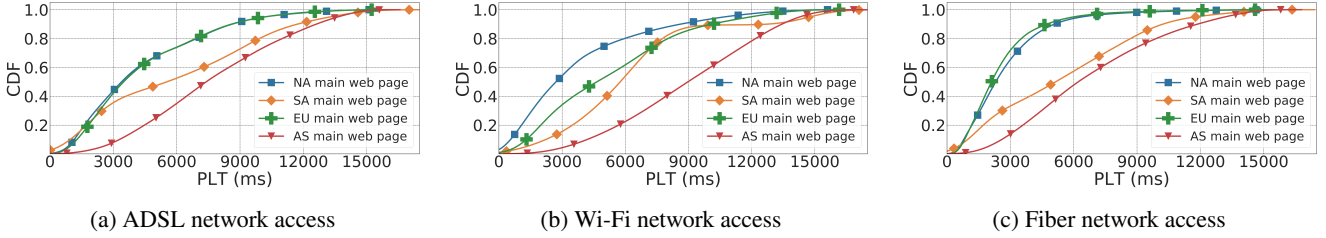


Figure 11: PLT loading time


Figure 12: Impact of number of domains

Figure 13: PLT when requesting HTTP/1.1

5.2. Impact of the number of domains

When performing web browsing, the resources are downloaded from various domains (as discussed in section 4.2, from *Same-Origin* and *Non-Origin* domains). The number of domains contacted increases proportionally to the DNS lookup times and thus the overall loading times (for the TFVR or PLT). When a web page is located in North America or Europe, on average, resources are downloaded from 9 domains (with an overall DNS time of 316.09 ms) and when the main web page is in South America, resources are downloaded on average from 16 domains (with an overall DNS time of 1715.85 ms). In general websites being served by large number of domains belong to the *News* and *Shopping* category.

Fig. 12 illustrates the overall tendency regarding the number of domains through which resources are downloaded when requesting HTTP/2 and the corresponding loading time. This is represented as a heatmap where dark blue represents higher concentration of values and light blue lower concentration of values together with the corresponding Page Load Time. For instance, in Fig. 12a, there are plenty of websites having about 7-8 domains and offering a PLT of about 1500 ms, and very few websites having 30 domains for a PLT at about 3000 ms. When a web page is located in North America or Europe, the PLT loading time is good and time increases with the number of domains from which the resources are downloaded. When the main web page is in Asia, the PLT loading time increases proportionally to the number of domains (average of 3915 ms DNS time with the number of domains being 4) and the objects being mainly served in HTTP/1.1 increase blocking and waiting time.

5.3. Impact of ad blockers

Advertisement in web pages is nowadays naturally embedded and can decrease an end-user's QoE, regarding the

overall loading time of a website. From our measurements, when using an ad blocker (Adblock Plus), on average, the number of downloaded resources is reduced by 11.02%. It is decreased by 9.72% when the main web page is in North America, by 8.43% in Europe, by 11.84% in South America and by 14.10% when the main web page is in Asia. Websites belonging to the *Shopping*, *Kids and Teens* and *Games* categories have the most significant decrease in the number of downloaded objects and the PLT for websites belonging to these 3 categories are on average decreased by 39.96%. Regarding other website categories, blocked objects are mainly characterized as social network contents (e.g *Facebook*, *Twitter*, *LinkedIn*, etc.).

5.4. Impact of the network access

End-users may be served by different network service providers, along with different bandwidths and data communication technologies (e.g ADSL, Wi-Fi, Fiber). Our measurements reflect observed web browsing quality where

$$Bandwidth_{ADSL} < Bandwidth_{Wi-Fi} < Bandwidth_{Fiber}$$

The Fig. 13 depicts the observed PLT loading times when requesting HTTP/1.1 following different network access. For example, when the main web page is in North America, less than 80% of the measurements have a PLT less than 6901 ms for ADSL network access, PLT less than 6000 ms for Wi-Fi network access and PLT less than 4000 ms for Fiber network access, thus representing a reduction of the loading time of 42.03% when shifting from ADSL to Fiber network access. When requesting the QUIC protocol, as shown in Fig. 14, the end-user's QoE increases proportionally to bandwidth increase, independently of the main web page continent location. On average depending on the network access (ADSL vs Fiber), an end-user's PLT is decreased by 30.25%.

A 6-month Analysis of Factors Impacting Web Browsing Quality for QoE Prediction

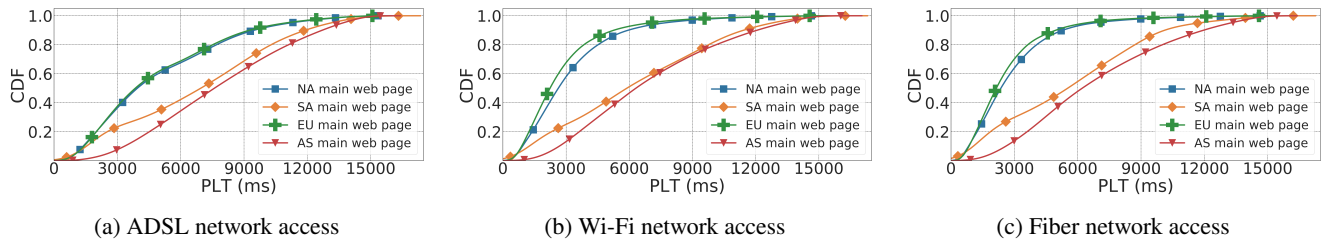


Figure 14: PLT when requesting QUIC

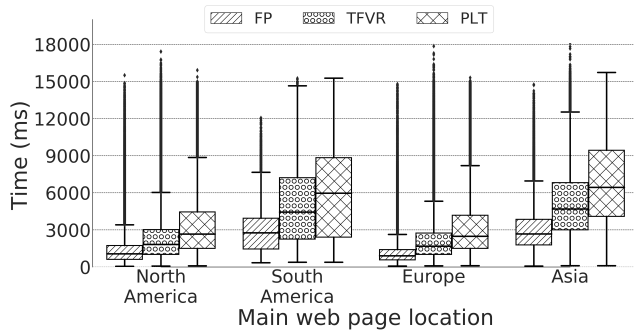


Figure 15: Overall loading times

Increased end-user QoE is tightly linked to the corresponding network access and requested protocol. When requesting HTTP/2 or QUIC, irrespective of the main web page location, web pages' loading times are decreased on average by 19.73% from ADSL to Wi-Fi, 16.02% from Wi-Fi to Fiber and 30.25% from ADSL to Fiber.

5.5. Impact of main web page location

Fig. 15 depicts the overall web pages' loading times, grouped by estimated continents location of the home page. The overall centered (median) time follows the rule $FP < TFVR < PLT$. Being in France when performing those measurements, we noticed that the overall loading times for a European end-user are smaller for the websites located in North America and Europe than for those located in South America and Asia. The 25th percentile and 75th percentile are denoted by $Q1$ and $Q3$.

When the main web page is located in North America, less than 50% of the measurements have a PLT less than 2962 ms, $Q1$ and $Q3$ are respectively at 1753 ms and 4868 ms. The parameters inducing the outliers are due to high number of domains (mainly *Non-origin*), high amount of downloaded objects and objects served over HTTP/1.1. The extreme outliers are for those objects downloaded from South America and Asia. When the main web page is located in South America and Asia, the observed times are higher in general but the number of outliers reduced since more resources are downloaded from the same continent of the main web page domain and the upper limit closer to the defined timeout for every measurement.

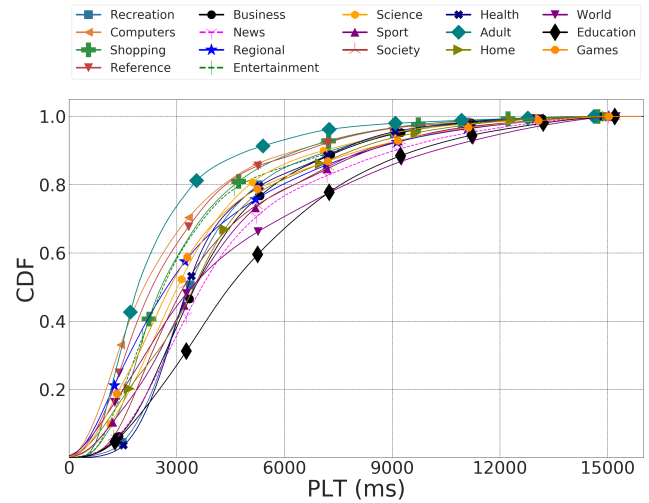


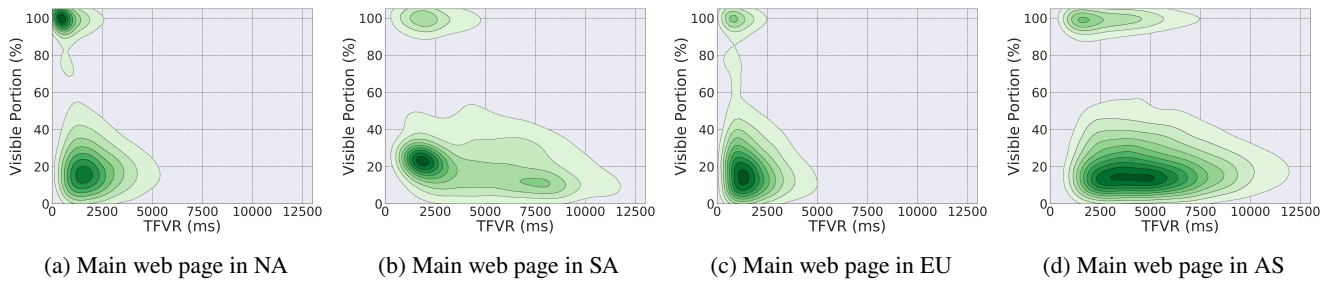
Figure 16: PLT for different websites' categories

5.6. Impact of websites' referenced categories

Websites are all different among them composed of a wide range and number of objects. Following their content, they are referenced as belonging to different types of categories (e.g Alexa¹⁷, QuantCast [46] or Web Filter¹⁸). In our study, we make use of *Alexa* referenced category listing where websites are classified upon 17 different categories. The Fig. 16 shows the overall observed PLT for different categories. We can observe that the CDF is similar for many categories except for 2 of them (*Adult* and *Education*). For instance, for most categories, for 50% of our measurements, the observed PLT is about 2500-3000 ms. Websites belonging to the *Computers*, *Reference* and *Shopping* category have loading times being close among them (compared to websites belonging to the *Recreation*, *Business* and *News* category) mainly due to objects MIME types composing the web page. There is the biggest gap between the *Adult* and *Education* category. While for less than 75% of our measurements, websites belonging to the *Adult* category have a PLT less than 3054 ms, websites belonging to the *Education* category have a PLT less than 6816 ms. While these two categories download on average the same types of objects (mainly *images* and *videos*), from our analysis in section 4.4 and 4.1, the main difference which results in a higher observed PLT is that objects for *Adult* categories are mainly downloaded

¹⁷<https://www.alexa.com/topsites/category>

¹⁸<https://fortiguard.com/webfilter/categories>


Figure 17: Impact of visible portion on TFVR

in HTTP/2 protocol (HTTP/1.1 for *Education* category) and that images and videos for the *Education* category are bigger in size.

We can then see that the category can play a role in the web browsing quality, but it is limited and less than the sizes of downloaded objects and the protocol through which they are downloaded which contribute most of the time to a higher PLT value.

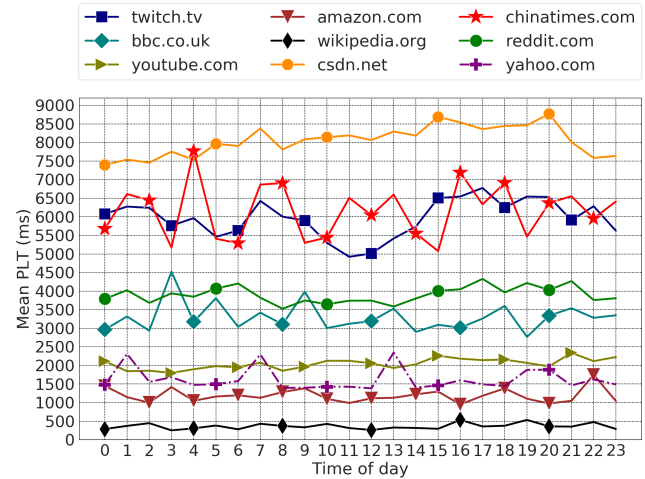
5.7. Impact of visible portion on its corresponding loading time

Our measurements have been performed following different web browsers' window sizes and the Fig. 8 has shown that depending on the main web page continent location and corresponding web browser window size, an end-user might have a larger overview of the web page without scrolling. We focus in this section on the impact of this visible portion on the time to load it. The default logical assumption would be that the time to load λ % of a web page would be proportional. The Fig. 17 (Heatmap : Dark green represents higher concentration of values and light green lower concentration of values together with the corresponding TFVR) depicts the concentration of websites following their visible portion (without scrolling the web page) and corresponding time to be loaded (TFVR). As discussed in section 4.4, websites having their main web page in North America share the particularity of having higher visible portions (mainly *Search-Engines*) and the Fig. 17a show that the corresponding TFVR ranges from 400 ms to 700 ms when the visible portion is 100% and ranges from 1200 ms to 1875 ms when the visible portion is between 11% and 20%. The Fig. 17d depicts websites whose main web page is in Asia, where we can see that these web pages have a visible portion massively ranging from 13% to 17% with loading times between 2700 ms and 5000 ms (apart from a limited number of web pages having a visible portion of 100% and TFVR between 1815 ms and 2104 ms).

The TFVR is not proportional to the visible portion since different actors contribute to this loading time (type and number of objects in the visible portion, the network download time, etc.).

5.8. Impact of time of day

Our measurements have been performed round the clock all day long, since following different times of the day a web-


Figure 18: Loading time of different websites at different times of the day

site might be visited by a larger number of end-users, and thus increasing the time needed for the servers to deliver different objects. Furthermore, the overall network state to reach the remote servers might be overloaded (e.g peak hours versus off-peak hours). We thus assess in this section the impact of the time of day on the perceived page load time. The Fig. 18 depicts a set of websites' loading times at different times of the day. While some websites' loading time stay relatively the same all day long (e.g *wikipedia.org*), other websites depending on their category (thus content) may have their inner structure change several times per day (e.g *News: chinatimes.com* or *Entertainment: twitch.tv*). Our measurements have been performed in Europe, and we can notice that the website *chinatimes.com* average PLT increases drastically at 04H CET (12H in Asia) and 08 CET (16H in Asia). We can thus suppose following these times of the day in Asia that the website has a higher visit rate in Asia, and an European end-user experiences the side effects. In overall, we can notice that between 12H CET - 14 CET or 20H CET - 22H CET, the average loading times perceived by end-users also increase which is most of the time due to the network state.

Web pages loading times are impacted following different times of the day mainly due to their visit rate (web servers impacted) and network state (overloaded during peak hours).

Parameters	FP	TFVR	PLT
Main web page location	✓	✓	✓
Requested protocol		✓	✓
Round Trip Time	✓	✓	✓
Website category	✓	✓	✓
Number of objects	✓	✓	✓
Main HTML page size	✓	✓	✓
Size of objects		✓	✓
Types of objects		✓	✓
Visible Portion			✓
Number of domains		✓	✓
Use of ad blocker		✓	✓
Time of day	✓	✓	✓
Network access	✓	✓	✓

Table 1
Parameters influencing web browsing quality

The corresponding loading times might also fluctuate depending upon the website category since the number of downloaded objects (and MIME type and size) might increase.

5.9. Which parameters can influence Web Browsing quality?

Based on our statistical measurements analysis, the Table 1 represents the different parameters to be taken into consideration when investigating the FP (First Paint), TFVR (Time for Full Visual Rendering) and PLT (Page Load Time) loading times. As per our geographic location (Europe), main web pages located in South America and Asia bring higher loading times (compared to main web pages in North America and Europe). The network access and requested protocol are tightly linked to an increased quality. The number, size and type of objects and the main HTML page size have a strong link with the website's Alexa-referenced category listing (e.g *Search Engine* category websites are composed of small number of objects of small size, *News* category websites are longer in *scrollHeight*, thus composed of many objects and served by a large number of domains, etc.). Finally, other factors like the time of day or the visible portion can have an impact on the quality but at a lower degree.

6. Machine Learning Techniques to predict web browsing quality

With our statistical analysis, we are able to know the factors impacting the web browsing quality, but we can not manually identify the thresholds or the values leading to a good or a bad quality. For this, we have applied different Machine Learning techniques on our dataset, namely Clustering (and BiClustering), Covariance or Density estimation, Principal Component Analysis (PCA) and Decision Trees. As identified in the previous sections, the factors influencing QoE are linked together and decision tree is revealed to be the most adequate non-parametric supervised learning method. In our study, decision tree rules are detected from 40% of the entire dataset that we denote by *training dataset* and the other 60% is used to validate the rules, denoted by

validation dataset. Indeed, defining rules with only the Top 500 or Top 1,000 Alexa is not efficient due to the diversity of the websites structure in the Top 10,000. The decision tree enables us to predict the estimated end-user quality by applying decision rules which are computed from our dataset.

6.1. Decision Tree based on satisfaction degrees

Several studies regarding the MOS (Mean Opinion Score) during web browsing sessions [47, 48, 32, 37] provide visible web page loading times. Table 2 presents the different degrees of satisfaction based on end-user sociological perceived feelings [49] coupled to these MOS studies. *Instant response* indicates a high responsiveness from the visited web page, *Seamless response* indicates that the end-user is happy with the overall experience, *Average response* indicates that the end-user feels the delay for the web page to load acceptable, *Critical response* indicates that the end-user strongly feels the bad side effects of the long web page loading and *Bad response* indicates that the end-user is not happy at all and can give up the browsing.

Based on the time values mentioned for these satisfaction degrees and the values of the TFVR for our measurements, we hereafter expose the corresponding sets of rules obtained from Decision Trees applied to our *training dataset* for the 5 classes. The full obtained decision tree is represented by 184 different nodes.

Instant response. Our measurements do not have any TFVR loading time lower than 100 ms and make this class unnecessary.

Seamless response. 24.32% of the *training dataset* has a TFVR in this range and the main impacting factors for this classification are the main web page located in North America or Europe, a low RTT value for the main web page, QUIC Repeat as requested protocol and a Fiber network access.

Average response. 30.67% of our *training values* belongs to this class and the main factors are the main web page located in North America or Europe, the requested Internet protocol being HTTP2, QUIC or QUIC Repeat, a Wi-Fi network access, the use of an ad blocker and RTT value between 18.65 ms and 101.5 ms.

Critical response. 43.78% of the *training measurements* have a TFVR in this class, impacted by the main web page located in Europe, South America or Asia, the visible portion between 22.76% and 41.39% (these web pages have a larger *scroll height*), the objects served by various content servers mainly located in Asia and Wi-Fi or ADSL as network access.

Bad response. 1.23% of the *training dataset* is classified as *Bad response*, mainly because of the use of Wi-Fi network access and HTTP/1.1 as requested protocol.

Once this decision tree has been built based on the *training dataset*, we evaluated it with the *validation dataset*. The Table 3 depicts the obtained classification confusion matrix, where the diagonal represents the percentage of measurements correctly predicted. We can see that 84.79% of the predictions are good, but more than 15% of the validation dataset is wrongly predicted. Looking at the matrix, the val-

Satisfaction degrees	Loading Times (ms)
Instant response	< 100
Seamless response	100 - 1000
Average response	1000 - 3000
Critical response	3000 - 10000
Bad response	> 10000

Table 2

User satisfaction degrees, based on [49]

Predicted class	Actual class				
	Instant	Seamless	Average	Critical	Bad
Instant	0	0.15%	0	0	0
Seamless	0	22.21%	1.60%	0	0
Average	0	1.96%	29.01%	8.07%	0
Critical	0	0	0.04%	32.35%	0.01%
Bad	0	0	0.02%	3.36%	1.22%

Table 3

Classification confusion matrix of the *validation dataset* based on user satisfaction degrees

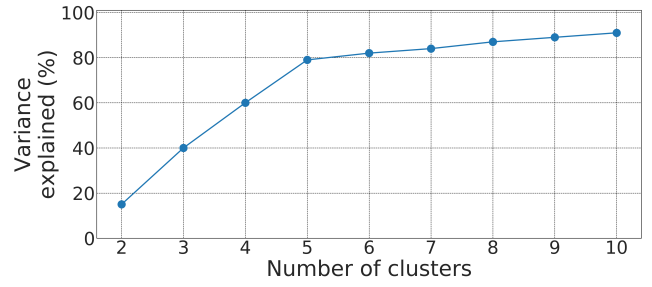
ues identified in Table 2 and the real TFVR values, we can say that the *Instant Response* class is unnecessary (no measurement in this class) and that the prediction error rate for the *Critical response* class is important (about 10%) because the loading time range is too wide.

6.2. Decision Tree based on estimated satisfaction degrees from clustering

Having seen that the proposed classification of the satisfaction degrees from literature is not optimal for current Web Browsing experience, we decided to define a new one, based on our huge dataset of web browsing measurements on the top 10,000 Alexa web sites. We thus look for the best satisfaction degrees using clustering (K-Means) to identify the different classes. The KMeans algorithm divides a set of samples X into K disjoint clusters C , where each cluster is described by the mean μ_j of the different samples in the cluster itself. In order to determine the value K , we use the *Elbow method* where we assess the percentage of explained variance (ratio between-group variance to the total variance) as a function of the number of clusters. As seen in Fig.19, the value 5 seems to be the good *Elbow Criterion*, and using it, we can identify the 5 clusters representing the different satisfaction degrees, illustrated in Table 4. The first and second satisfaction degrees from Table 2 have been merged into one degree and the *Critical response* satisfaction degree is distributed and split into two degrees. The estimated satisfaction degrees illustrated in Table 4 are more uniformly distributed, compared to Table 2.

We hereafter describe the impacting factors leading to the classification of one measurement into one class, learned from our *training dataset* by the decision tree model, represented by 176 different nodes.

Good response. 23.32% of the *training dataset* has a TFVR in this range and the main factors are the main web


Figure 19: Explained variance

Estimated satisfaction degrees	Loading Times (ms)
Good response	< 1232
Fair response	1232 - 3486
Moderate response	3486 - 6715
Worse response	6715 - 9281
Poor response	> 9281

Table 4

Estimated satisfaction degrees derived from our measurements

page located in North America or Europe, a low RTT and number of domains serving contents from North America or Europe, with replies delivered over the QUIC protocol.

Fair response. 27.31% of the *training measurements* are classified in this class and the main impacting factors are namely the main web page located in North America, a RTT value less than 105.5 ms, a Wi-Fi or Fiber network access, resources downloaded from North America, Europe or Asia in HTTPS, together with a low number of domains serving contents.

Moderate response. 31.26% of our *training dataset* leads to *Moderate response*, mainly based on the main web page located in Europe or Asia, the requested Internet protocol being HTTP/1.1, HTTP/2 or QUIC, the visible portion of the websites less than 13.25% and objects delivered from Asia or South America.

Worse response. 12.09% of the *training dataset* has a TFVR in this range with the main factors being the main web page located in South America or Asia, the number of downloaded resources between 45 and 85 (mainly downloaded from Asia), RTT value greater than 185.5 ms and the number of domains from Asia greater than 4.

Poor response. 6.02% of the *training measurements* lead to a poor quality, mainly because of the main web page located in Asia, HTTP/1.1 used as requested protocol, a high number of downloaded objects and the use of an ADSL network access.

We evaluate the accuracy of our decision tree with the rest of our dataset (i.e., 60% of our measurements) and the Table 5 depicts the obtained classification confusion matrix when applying the obtained rules on this *validation dataset*. We can see, looking at the diagonal representing the percentage of measurements correctly predicted, that our rules can efficiently predict 94.17% of the dataset. Only 5.83% of the *validation dataset* is wrongly predicted, which is 2.61 times

Predicted class	Actual class				
	Good	Fair	Moderate	Worse	Poor
Good	22.19%	0.04%	0	0	0
Fair	1.13%	25.17%	0.82%	0	0
Moderate	0	2.10%	29.22%	0.43%	0
Worse	0	0	1.20%	11.63%	0.06%
Poor	0	0	0.02%	0.03%	5.96%

Table 5

Classification confusion matrix of the *validation dataset* based on estimated satisfaction degrees

Predicted class	Actual class				
	Good	Fair	Moderate	Worse	Poor
Good	6.51%	0.16%	0	0	0
Fair	0.76%	21.09%	0.72%	0	0.02
Moderate	0.01%	1.96%	35.02%	0.12%	0.01%
Worse	0	0	3.60%	17.74%	1.03%
Poor	0	0	0	1.21%	10.04%

Table 6

Classification confusion matrix to validate the accuracy of our rules-based model, based on estimated satisfaction degrees

less when compared to the rules-based model obtained in section 6.1. We can then think that this model is better.

6.3. Accuracy of our rules-based model

In order to verify the correctness of the obtained decision tree from section 6.2, we have performed in February 2019 measurements on the Alexa websites ranging from rank 10,000 to 15,000. The dataset sums up to the measurement of 4861 never-assessed before distinct websites, which represent 2.7 Million different measurements. The Table 6 illustrates the obtained classification confusion matrix for these measurements when applying our rules-based model.

Among our measurements, 6.51% of the measurements provide a *Good response* (low RTT and small number of objects), 21.09% for *Fair response* (low RTT and main web page in Europe), 35.02% for *Moderate response* (large number of domains serving contents from Europe and Asia), 17.04% for *Worse response* and finally 10.04% of the measurements yield a *Poor response* (high HTTP/1.1 reply distribution and objects mainly delivered from South America and Asia).

In short, 90.4% of the overall new dataset was correctly predicted. This is a bit less than with the *validation dataset*, but it is related to websites which have never been accessed before, in contrast to the *validation dataset*, composed of websites being also in the *training dataset*. We can then conclude that our rules-based model can efficiently predict web browsing quality for any website for an end-user located in France.

We have presented in this paper the results of the analysis based on our measurements, performed by the probes in France (Europe). Our model has been proved to be correct for this configuration but it has to be adapted to other situations, e.g., end-user in another location. Indeed, as seen in Fig. 1a and Fig. 2, when visiting different websites having

their main web page located in specific continent-geographic locations, resources are downloaded from different continents (e.g for a European end-user visiting a web page in Asia, resources are downloaded from Europe, North America and Asia), which impacts the quality. As depicted in Table. 1, the impact of parameters to be re-assessed will be the Round-Trip-Time (network path taken through different Asynchronous Systems), number and types of objects (mainly due to advertising), the number of domains (specifically the location of web servers delivering content), time of the day and corresponding network access (the throughput offered by network operators from different regions are different).

7. Conclusion and Future work

In this paper we have shown the importance of taking into account diverse parameters to better quantify and qualify web browsing. We have used all the web metrics identified by the W3C or the research community and real on-market web browsers together with user-representative residential network access. Our study has brought light on the wide range of factors which can improve or decrease an end-user's web browsing quality. The identified impacting factors are then used as inputs to a rule-based model obtained from Decision Tree, in order to efficiently predict the web browsing quality.

Our measurements have been performed in France and an ongoing and future work is focused on performing measurements from different locations and using different network providers all around the world, to confirm the impacting factors to be taken into consideration, to refine the estimated satisfaction degrees for end-users' perceived web browsing quality and to validate our model. The obtained loading times contributing to the different estimated satisfaction degrees will also be assessed through a MOS study with real end-users.

8. Acknowledgement

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APPENDIX

Indicators	
wwwName	Assessed website name
ranking	Alexa referenced ranking
preferredProtocol	The requested protocol
addBlock	The use (or not) of an adblocker
netwlface	The used network interface (ADSL, Wi-Fi, Fiber)
timeDay	Time measurement performed
browserWidth	Width of the used browser
browserHeight	Height of the used browser
pingValue	Round Trip Time upon main web page
visiblePortion	Visible portion of the web page at first glance(no scrolling)
mainWWWLocation	Main web page continent location
h1Share	HTTP/1.1 overall replies distribution
h2Share	HTTP/2 overall replies distribution
hqShare	QUIC overall replies distribution
pushShare	SERVER PUSH replies distribution
nbRes	Number of downloaded objects
nbObjNA	Number of objects downloaded from North America
nbObjSA	Number of objects downloaded from South America
nbObjEU	Number of Objects downloaded from Europe
nbObjOrigin	Number of objects downloaded from <i>Same-Origin</i> server
nbObjNonOrigin	Number of objects downloaded from <i>Non-Origin</i> server
nbDomains	Number of domains serving contents
nbDomNA	Number of domains in North America
nbDomEU	Number of domains in Europe
nbDomAS	Number of domains in Asia
h1ShareBFP	HTTP/1.1 replies distribution before the First Paint
h2ShareBFP	HTTP/2 replies distribution before the First Paint
hqShareBFP	QUIC replies distribution before the First Paint
pushShareBFP	SERVER PUSH replies distribution before the First Paint
h1ShareBTFVR	HTTP/1.1 replies distribution before the TFVR
h2ShareBTFVR	HTTP/2 replies distribution before the TFVR
hqShareBTFVR	QUIC replies distribution before the TFVR
% Obj before FP	Percentage of objects downloaded before FP
% Obj before TFVR	Percentage of objects downloaded before TFVR
categoryType	Website category referenced by Alexa

Table 7
Decision Tree main factors' acronyms