Internet speeds and latency changes around the world during COVID-19 pandemic (2019-2021)

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Manish Kumar Mishra Peshmerge Morad
Nischal Neupane Wouter Bezemer

ABSTRACT. In this paper we demonstrate efficient and fast methods of labeling large amounts of geometric data with their corresponding country to visualize how the internet speed and latency have changed around the world leading up to and during the COVID-19 pandemic. We found that the rate at which internet speeds have improved have increased after the pandemic started in 2020, and we certainly see a correlation between the COVID-19 pandemic related restrictions and the rapid increase of internet speeds around the world.

Keywords: Ookla dataset, Internet speed, Big Data, COVID-19

1 Introduction

The Coronavirus disease (COVID-19) pandemic (3) has affected everyone in the world. World governments have imposed lockdown and social distancing measures to fight the virus outbreak. Those measures have changed how we live, work, study, and communicate. Although the pandemic caused millions of deaths, it made the unimaginable real, and it helped shape a new reality where almost everything happens online. Tele-Work, tele-health, online shopping, and online learning have become the norm during the pandemic (6)(8). However, this change would not have been possible without the existence of the internet. Because of this offline-to-online transition in work and study, internet speed has become a vital part of our personal and professional life (4).

Internet connections can be categorized into two main categories, fixed-internet, and mobile-internet connections. Fixed-internet is the type of connection where the internet is provided to the end-user on a fixed physical location using internet cables (coaxial and fiber optics). On the other hand, Mobile-internet is provided to the end-user using 3G, 4G, and 5G cellular networks.
This paper tries to uncover any possible correlation between COVID-19 and internet speed and latency change from 2019 until 2021. We firmly believe there is a positive change in internet speed and latency. The internet has become essential in enabling people to stay home while maintaining the same availability for work, study, or other social activities.
To make the research more specific, we have formulated the following question: **How have internet speed and latency changed around the world during the COVID-19 pandemic (2019-2021)?**

This paper is organized in the following way. Section 2 gives a brief overview of related works that have already been done in the field. Section 3 will focus on the dataset we have used. In addition, we describe the pre-processing and post-processing steps we have carried out to make the dataset suitable for further data analysis. Section 4 will show our findings and results. In Section 5 we present the statistical analysis for our results. In addition, we mention the the drawbacks of our approach. Finally, Section 6 discusses the results we have obtained from the dataset.

2 Related work

A considerable amount of studies has been published on studying internet speed. Some of them has been focusing on the social and economic implication of the difference between the broadband access speed between countries or within the same country between rural and urban areas (10) (12) (5). Other studies have been carried out with the aim of visualizing the internet speeds in different parts of the world. In (9), researchers have tried to visualize the internet speed in Asia and the Pacific to gain insights into trends in internet download speed in the Asian-Pacific region. In (11), researchers have collected internet usage data to measure work-form-home (WFH) rates with regards to the Covid-19 life disruption.

3 Methodology

3.1 Dataset

The dataset used is The Internet Speed Dataset provided by Ookla (2). The dataset provides two variations of dataset. The two variations are separated to two files in *parquet* form, which is native to *Spark* framework which was used in this project. The two file variations were as follows:

- **performance_mobile_tiles** - These are the tiles containing tests taken from mobile devices that have access to GPS-quality location and a cellular connection type (e.g. 4G, 5G).
- **performance_fixed_tiles** - These are the tiles containing tests taken from a fixed/mobile devices that have access to GPS-quality location and a fixed connection type (e.g. WiFi, Ethernet..)

Both variations of dataset are comprised the following columns:

Field name	**Type**	**Description**
quadkey	Text	The quadkey representing the tile.
tile	Text	Well Known Text (WKT) representation of the tile geometry.
avg_d_kbps	Integer	The average download speed of all tests performed in the tile, represented in kilobits per second.
avg_u_kbps	Integer	The average upload speed of all tests performed in the tile, represented in kilobits per second.
avg_lat_ms	Integer	The average latency of all tests performed in the tile, represented in milliseconds.
tests	Integer	The number of tests taken in the tile.
devices	Integer	The number of unique devices contributing tests in the tile.

Table 1: Dataset columns as described by Ookla

And are organized into quarters. The data consists of three years - 2019, 2020, and 2021, each represented by four quarters - Q1, Q2, Q3, and Q4.

The data inside in the column *tile* is geographical information at zoom level 16 which equates to approximately 610.8×610.8 meters at the equator (18 arcsecond blocks). The data is represented in WGS 1984 (EPSG:4326) [1]. The data inside the column follows the Well-known text (WKT) representation for representing the vector geometry objects. The WKT has multiple object types such as Point, LineString, Multipolygon, and Polygon.
In our case, the column contains only Polygon objects. The Polygon consists of five coordinate points defined in a counterclockwise order. For example the following polyogon corresponds a polygon shaped location in Nanchang County, Jiangxi, China :

```
POLYGON((116.098022460938 28.6713109158808, 116.103515625 28.6713109158808,
116.103515625 28.6664911769866, 116.098022460938 28.6664911769866,
116.098022460938 28.6713109158808))
```

Dataset part	Rows	Tests	Size in GB
performance_fixed_tiles	75546804	1662003528	6.4 GB
performance_mobile_tiles	47813851	335382158	4.0 GB

Table 2: Dataset size categorized per type

3.1.1 Dataset size

3.2 Building a database of countries

Multiple approaches were explored during the task of building a database of countries using the *Tile* information provided through the dataset - in order to make data aggregation possible, such as grouping, averaging, etc.

3.2.1 Pre-processing Approaches

Some of the approaches we attempted involved preprocessing data in order to minimize the dataset and avoid working with extremely large amount of data to feed into APIs or for dictionary lookup, which will be discussed further in the next few paragraphs. One of the preprocessing step, joining the datasets by *quadkey* was done on each year of the data - 2019, 2020, and 2021. Since *quadkey* is unique to a tile, we inner-joined the dataframes involving multiple years and quarters in order to find a common dataset among all 3 years and their respective quarters. This minimized the dataset from its original length of approximately 21 million rows to 6.5 million rows, which was far more feasible to work with. In the following paragraphs, the different approaches taken on the preprocessed data to build the database of countries is discussed.

GeoPy Approach One of the approaches involved using a Python package called GeoPy [2]. This package has a nicely defined wrapper for almost all online (reverse-)Geocoders APIs such as Google Maps, Bing Maps, or Nominatim. Nominatim is an open-source tool to search OpenStreetMap[3] (OSM) data by name and address and to generate synthetic addresses of OSM points (reverse geocoding). To make the build process quick and efficient, we reduced the Polygon points in the tile column into one coordinate point (longitude, latitude). Then truncated all numbers behind the decimal point.

This process had a few downsides. One downside involved the time it took for the data to be parsed from the API. Due to the limitation invoked by the APIs, we were only allowed to query once every second. Thus, 13K data points resulted in a total query time of approximately 2 hours to build the dataset.

However, another downside was the truncating of latitude and longitude information, where we lost some precise information. However, this did not affect our end goal. Since we were interested in countries rather than exact locations like a city or street, losing precise coordinates did not make a noticeable difference in the results compared to what we expected. Nevertheless, by following those steps, we managed to get a curated list of coordinate points where filtering out the duplicates was quite simple. That resulted in 13 thousand unique locations obtained from the whole dataset.

GeoPy approach using a locally hosted Geocoder API To overcome the mentioned downsides in the previous paragraph, we have decided to build world maps locally and run a locally hosted instance of Nominatim on one of our laptops. One of the most outstanding features of Nominatim is that it can be installed on any machine. There are multiple ways of doing that, including using Docker [4]. By running the Docker instance, a fully configured instance of Nominatim runs locally.

[1] WGS stands for World Geodetic System which is a standard used in cartography and satellite navigation (GPS)
[2] https://geopy.readthedocs.io/en/stable/
[3] OpenStreetMap is a free, editable map of the whole world that is being built by volunteers primarily from scratch and released with an open-content license.
[4] https://github.com/mediagis/nominatim-docker

Unfortunately, that does not mean having access to the whole world map or a specific region. The world or specific regions maps must be downloaded separately. In terms of Nominatim, those maps are called OSM data extracts. Geofabriek [5] provides data extracts. Those extracts are updated daily, enabling us to keep the running instance up to date. Fig. 1 shows those data extracts with their sizes and the available formats of each data extract. The total size of the whole world map is around 56GB. Those data extracts could be downloaded separately and added to the Nominatim instance running locally. In addition, they could be merged into one big extract using tools like Osimium [6]. During the import process of those data extracts into the Nominatim, a couple of

Sub Region	Quick Links			
	.osm.pbf		.shp.zip	.osm.bz2
Africa	[.osm.pbf]	(5.0 GB)	✖	[.osm.bz2]
Antarctica	[.osm.pbf]	(31.0 MB)	[.shp.zip]	[.osm.bz2]
Asia	[.osm.pbf]	(10.5 GB)	✖	[.osm.bz2]
Australia and Oceania	[.osm.pbf]	(947 MB)	✖	[.osm.bz2]
Central America	[.osm.pbf]	(503 MB)	✖	[.osm.bz2]
Europe	[.osm.pbf]	(24.6 GB)	✖	[.osm.bz2]
North America	[.osm.pbf]	(11.1 GB)	✖	[.osm.bz2]
South America	[.osm.pbf]	(2.7 GB)	✖	[.osm.bz2]

Figure 1: World OSM data extracts and their sizes in MB's on https://download.geofabrik.de/

parameters can be adjusted to specify the details those extracts will provide, like *style* which could have different values. By choosing, for example, *admin* only the administrative boundaries and places will be imported. This ensures that fewer GB's will be used and will require significantly less time to complete the import process. Table 3 shows needed time and disk space for each import style in case the whole world map is being imported into the Nominatim instance locally. Unfor-

style	**Import time**	**DB size**	**after drop**
admin	4h	215 GB	20 GB
street	22h	440 GB	185 GB
address	36h	545 GB	260 GB
full	54h	640 GB	330 GB
extratags	54h	650 GB	340 GB

Table 3: Import style options and the time and size implications as reported on (1)

tunately, we could not proceed with this approach due to time and resources constraints. Those numbers are applicable when using a powerful machine with 64GB RAM, 4 CPUs, and NVME disks (1). Those numbers will triple on our laptops because we have fewer resources than those mentioned.

Dictionary-lookup Approach Even though the *GeoPy Approach* resulted in a well-formed solution, we noticed some issues with it - first, the time for building the dataset was far too long. Even though the dataset only needed to be built once, we wanted to minimize the time it took to build the dataset. Second, the truncating of latitude and longitude caused some coordinates to point to a location outside of the bounds of a country. For instance: the coordinate for Vatican City is:

[5] Geofabriek is a German company founded in 2007. Its focus is to provide free and community-maintained data like the OSM data extracts to be an alternative to paid maps providers.

[6] https://osmcode.org/osmium-tool/

$(41.903815, 12.453153)$ latitude and longitude, respectively. However, truncating the values results in a coordinate $(41, 12)$ which falls well into the Balearic Sea, far off from the *Tile* representing Vatican City.

To solve this issue, we approached the problem with the idea of eliminating the limiting API aspect of the *GeoPy Approach*. Using Geodata data package[7] which provided geojson polygons for all the world's countries, we were able to parse the *geojson* file into a dictionary consisting of the polygons and the countries. The Polygons were first converted from string to *Polygon* class using the Shapely[8] library available in Python and then added to the dictionary. This allowed for us to have a local copy of boundaries required to distinguish a country through their defined *Polygon*.

Using user-defined functions (udfs) in *Spark*, *Tile* column in each row was first parsed from string to *Polygon* class using the Shapely library as aforementioned. The *Polygon* for each *Tile* is checked if it falls **within** the country defined by its *Polygon*. If so, the respective country is returned, and if not, string $'N/A'$ is returned. This approach works rather well for the whole dataset and does not break the boundaries of the approximate country the *Tile* is from. The issue regarding the run-time still stands as this approach takes approximately 1 hour and 15 minutes on spark cluster due to the time-complexity of $O(m * n)$ where m is the length of the preprocessed data (6.5 million rows) and n is the length of the country dictionary (approximately 200).

3.2.2 Post-processing Approach

The following approaches involved processing the data after the country information was already known. Although the approach of preprocessing the data and reducing the data to only about 6.5 million rows seemed like a good choice, we realized a flaw where we did not consider how other columns such as *avg_d_kbps, avg_u_kbps..* would behave.

To meet our research goal for this project, we had to separate the data based on each year to look at their changes and/or differences. Joining them would cause unnecessary complications. Thus, we decided to approach the problem by looking at quarterly data separately for each year. We performed the approaches mentioned in the upcoming paragraphs first to build the column of countries based on *Tile* information for each row. The data was then grouped by country, where columns related to the download/upload speed and latency were averaged for each country. The columns related to the tests and the number of devices were summed to approximate how many data points each country has. The columns related to *Tile* and *quadkey* were dropped since we do not need that information anymore. Thus, the dataset after post-processing comprised 22 total data frames. Eleven related to *mobile_tiles* and other eleven related to *fixed_tiles*, each with approximately 200 rows representing the countries and six columns representing information regarding broadband speed test.

The following paragraphs detail the approach taken to build the dataset with country information.

GeoPandas Spatial Index Approach This approach is quite similar to *Dictionary-lookup Approach* where the Geodata data package was used with information regarding the polygons of all the world's countries. However, unlike the previous approach, we made use of GeoPanda's Spatial Index[9] which uses an R-Tree algorithm[10] for spatial indexing, which performs for average-case $O(\log(n))$ where n is the number of countries.

Instead of the naive approach, we were able to convert the country information to a geopandas dataframe and use spatial indexing on the Polygons of countries, allowing us to query all *Tile* information from each dataset very efficiently and quickly. This approach was, on average, a lot quicker than the naive method of iterating through the dictionary of countries and resulted in a runtime being reduced to an average of approximately 12 minutes - even with raw data consisting of more than 20 million rows as compared to the previous preprocessed data with 6.5 million rows.

[7] https://datahub.io/core/geo-countries
[8] https://shapely.readthedocs.io/en/stable/manual.html
[9] https://geopandas.org/en/stable/docs/reference/sindex.html
[10] https://en.wikipedia.org/wiki/R-tree

We then performed the above post-processing step for each quarter's data, bringing the Big Data we started with down to reasonably-sized data that can be worked with locally for processing and analyzing.

3.2.3 Other Approaches

Following the steps of Section 3.2.1 for preprocessing the data. Another method involving the use of GeoNames[11] which gave us access to a location dump generated by GeoNames, which consisted of over 12 million locations (cities, landmarks, etc..), each accompanied by their approximate latitude and longitude. The information of latitude and longitude were fed to a BallTree[12] model from Scikit-learn library, which allows for a fast generalization of the coordinates and allows for querying the nearest neighbors. BallTree model partitions data in a series of nesting hyper-spheres which wraps the Nearest Neighbors Algorithm, which works rather well for our application.

However, the model did not align very well with the *Tile* information we had access to. Since each *Polygon* consisted of multiple coordinates, we tackled the issue by using an approximate coordinate within the Polygon which was achieved by calculating the centroid[13] of the Polygon. The centroid points were then used to query the BallTree model for the nearest landmark/city using the Haversine[14] metric for distance calculation.

The runtime of this approach was approximately 15 minutes on spark cluster which was relatively quick and efficient. However, due to the approximate nature of this approach and the lack of consistency in the number of testing devices among the quarters and years, we realized that generalization of broadband speed within a particular landmark/location led to inaccuracy and turned out impossible. Due to this reasoning and the time constraint, we were not able to continue with this approach and were dropped in favor of *GeoPandas Spatial Index Approach.*

The code for our project can be found on GitHub [15]

4 Results

After we shrank the raw data down to country-level averages, we analyzed the data locally on our machines. We have used Microsoft Excel and Python to analyze and plot the changes in internet metrics. In Fig. 2, we present the plots for changes in internet speeds and latency worldwide. We see a steady increase in fixed and mobile upload speeds between the start of 2019 and the end of 2021. On the other hand, we observe that the download speeds for fixed devices have a steady increase until mid-2020, and then a sharp increase from thereon. In comparison, mobile download speeds have abrupt changes, yet an average increase. Coming to the worldwide average latency chart, we observe that mobile and fixed internet latency is declining. However, we do not observe any drastic decrease in latency in the time frame.

In Table 4, we tabulate the worldwide differences in average internet upload and download speeds and latency in percentages. We have divided the data into two halves, the first half represents the period between Q1 of 2019 and Q2 of 2020 and the second half between Q3 of 2020 and Q4 of 2021. We chose this split because the effects of the worldwide lockdowns and the shift to working from home started catching traction around Q2 of 2020. We can see a massive rise in fixed internet speed in the second half of the period, about 56.6% compared to only 15.9% in the first half. A similar observation can be made for the fixed upload speeds - 58.2% in the second half versus 29.7% in the first half.

We also present a world density graph of difference between the start (Q1 of 2019) and the end (Q4 of 2021) of our time frame in Appendix A.

[11] http://download.geonames.org/export/dump/

[12] https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.BallTree.html

[13] A centroid of a Polygon is a point in the center of a Polygon with approximately the same distance to all boundary points of the Polygon

[14] https://en.wikipedia.org/wiki/Haversine_formula

[15] https://github.com/peshmerge/managing_big_data_project

Figure 2: Worldwide average speed (left) and latency (right)

	Fixed		Mobile	
	First half	**Second half**	**First half**	**Second half**
Download	15.9%	56.6%	76.4%	76.0%
Upload	29.7%	58.2%	24.4%	37.5%
Latency	-25.7%	-17.1%	-20.6%	-10.5%

Table 4: Change in speed and latency around the world from 2019 Q1 to 2020 Q2 (first half) and from 2020 Q3 to 2021 Q4 (second half)

4.1 Internet speed changes in The Netherlands and China

In Fig. 3, we present the changes in internet speed in The Netherlands and China. The Netherlands shows a steady increase throughout for fixed and mobile internet, whereas China has a massive increase in the mobile download speed, outperforming the fixed download speeds right from Q1 of 2020. The mobile upload and fixed internet speed in China have a steady growth.

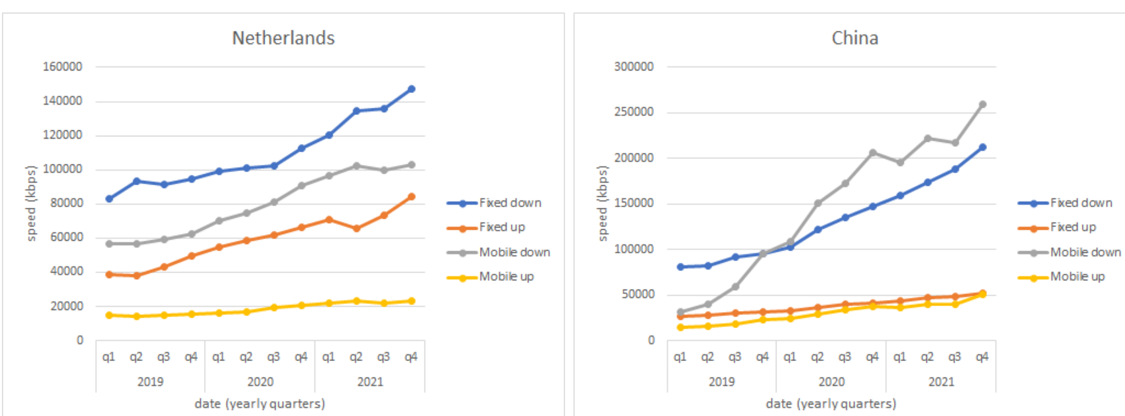

Figure 3: Comparison of broadband speed in The Netherlands and China

5 Discussion

In Section 4, we present a plot of worldwide average internet speed and latency and analyze the internet speed in The Netherlands and China in our time frame. From Fig. 2, we clearly see a rapid increase in internet speeds right after Q2 of 2020. The World Health Organisation (WHO) declared COVID-19 as a pandemic on March 11, 2020 (3) and soon, most countries around the world went into lockdown and started working from home. This timeline coincides with the trend of internet speeds we saw earlier.

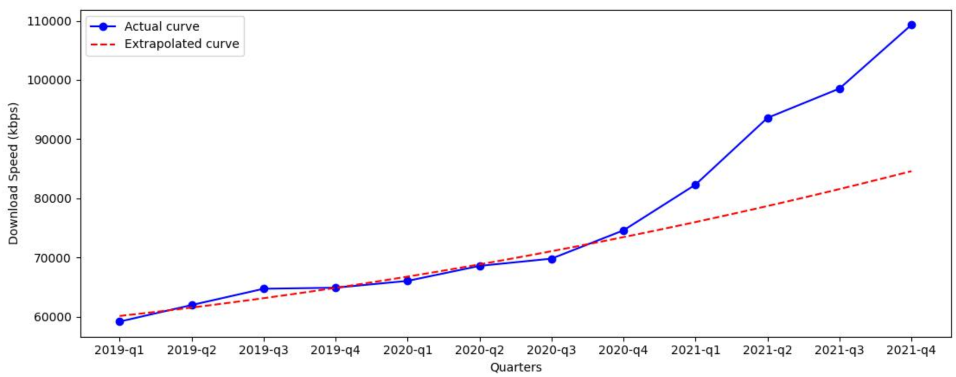

Figure 4: Worldwide average internet download speed for fixed connection extrapolated

In Fig. 4, we extrapolate the growth for the fixed connection internet download speed in the first half of our time frame (from Q1 2019 to Q2 2020). From the data we have obtained from Ookla, the increase of internet download speed for fixed connections from Q1 of 2019 to Q4 of 2021 is 84.67%, whereas, from the interpolated data, we only get an expected increase of 40.66%. In their analysis of internet speeds between 2017 and 2019 (7), Ookla reports an increase of 37.4% in the worldwide fixed download speed. This result aligns with our interpolated increase of 40.66%.

5.1 Limitations

The results so far look promising. However, there are a few limitations in our methodology of classifying tiles into their respective countries. Using the **GeoPandas Spatial Index Approach** (Section 3), some of the tiles were incorrectly labeled as $'N/A'$. These tiles partially lie in multiple countries, or do not lie within a country (for instance, with some part in the water bodies). Although this does not affect the worldwide averages, the country-wise data is not completely accurate. On a closer look, we find that about 3% of all the tiles were marked as such.

6 Conclusion

We started this project with a hypothesis about the correlation between the COVID-19 outbreak and internet speed and latency changes in 2019-2021 time period. From our findings in Section 4 and Section 5, we can clearly see a faster increase in the internet speeds around the world coinciding with the time when most of the countries had imposed lockdown due to COVID-19 related restrictions. This correlation is also strengthened by comparing the growth of internet speeds from previous years, and extrapolating the data we have from before Q3 of 2020. On the other hand, the decrease in internet latency was not as rapid. The change in latency was rather a steady decrease that could be a result of normal internet infrastructure developments.
However, a further verification of our results might be needed to ensure that the COVID-19 related restrictions are the cause of the rapid increase of internet speeds around the world.

References

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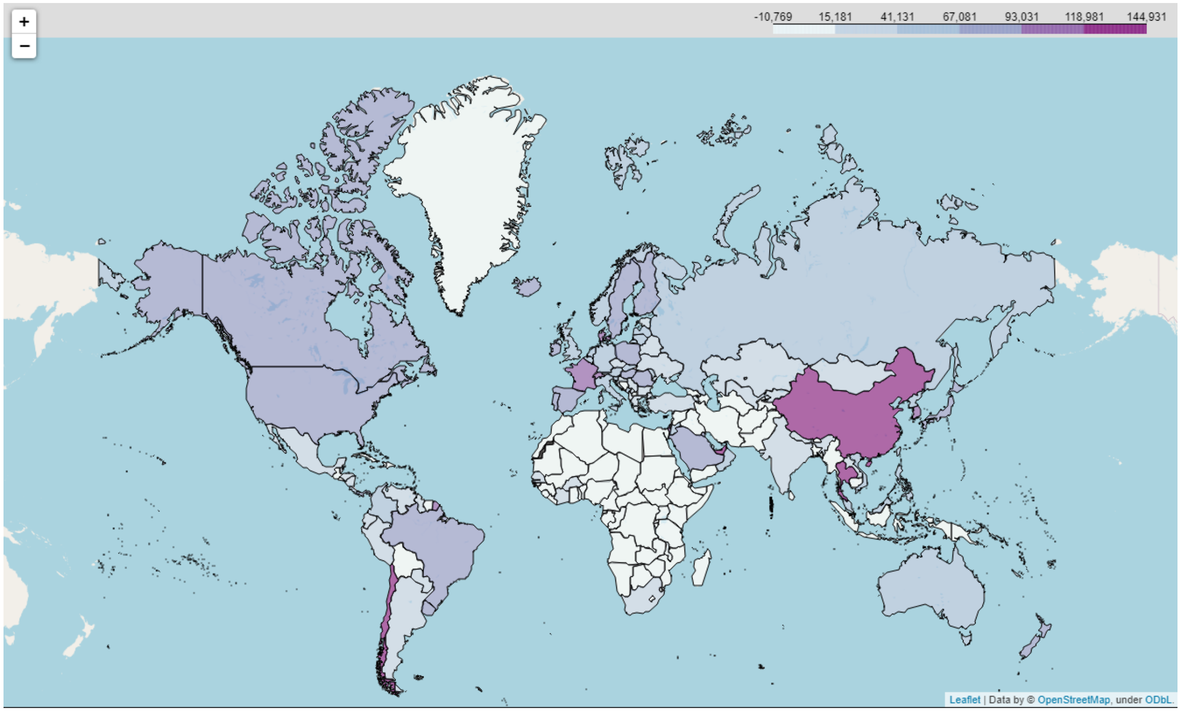
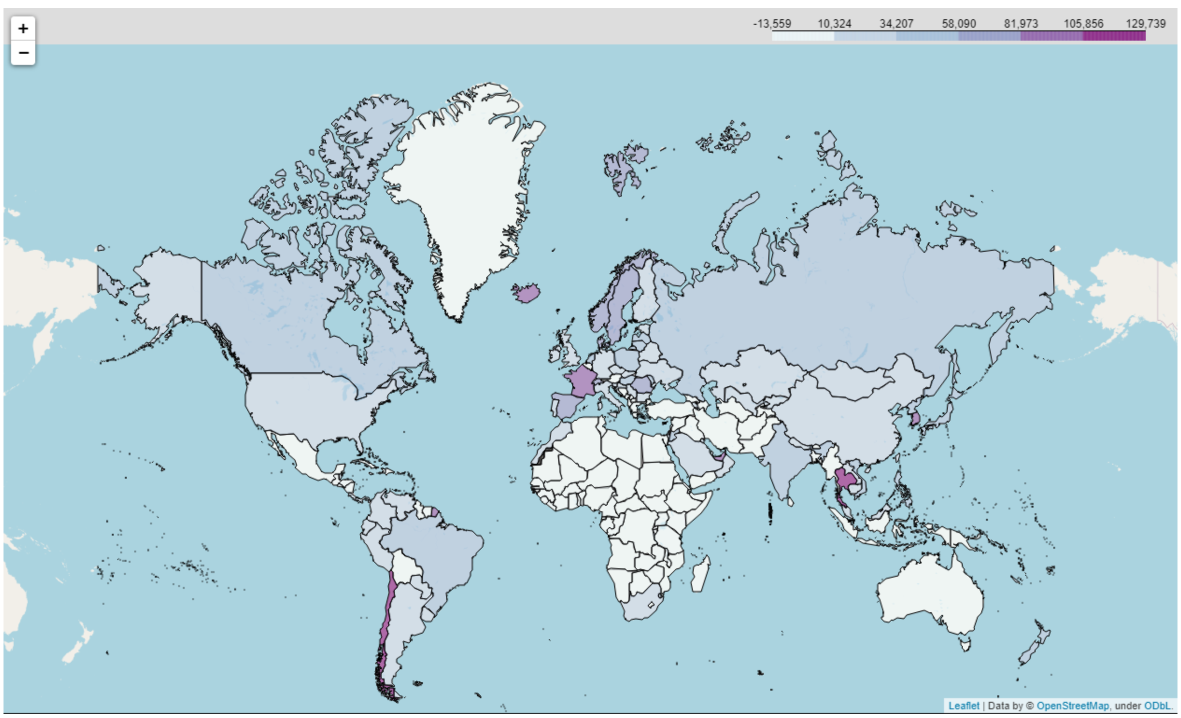
A Appendix

A.1 World Maps



(a) Fixed download



(b) Fixed upload

Figure 5: Density graph of change between Quarter 1 2019 and Quarter 4 2021

A.2 Top 10 list

A.2.1 Fixed Tiles

Ranking	Country	Speed(mbps)
1	Thailand	144.93
2	United Arab Emirates	144.32
3	Chile	142.71
4	China	132.31
5	Monaco	130.67
6	Hong Kong S.A.R.	116.61
7	France	111.05
8	Denmark	104.2
9	Israel	101.31
10	Switzerland	99.96

(a) Top 10 Countries with Highest Growth in fixed Average Download Speed

Ranking	Country	Speed(mbps)
1	Nauru	-10.77
2	Palau	-6.48
3	Gabon	-5.74
4	Sudan	-3.45
5	Samoa	-2.32
6	Comoros	-2.06
7	Niue	-1.7
8	Kenya	-1.61
9	Guinea Bissau	-0.97
10	Turkmenistan	-0.95

(b) Top 10 Countries with Highest Decline in fixed Average Download Speed

Table 5: Top 10 countries in Highest and Lowest difference in Fixed Average Download Speed between 2019 Quarter 1 and 2021 Quarter 4

Ranking	Country	Speed(mbps)
1	Thailand	129.74
2	Chile	126.3
3	Jersey	117.2
4	United Arab Emirates	102.49
5	South Korea	102.33
6	Monaco	89.45
7	Liechtenstein	88.78
8	France	86.96
9	Iceland	82.03
10	Romania	81.14

(a) Top 10 Countries with Highest Growth in fixed Average Upload Speed

Ranking	Country	Speed(mbps)
1	Nauru	-13.56
2	Niue	-10.89
3	Rwanda	-9.44
4	Antarctica	-4.62
5	Turkmenistan	-3.89
6	Palau	-3.66
7	Gabon	-3.4
8	Samoa	-3.21
9	Papua New Guinea	-2.54
10	Burundi	-2.4

(b) Top 10 Countries with Highest Decline in fixed Average Upload Speed

Table 6: Top 10 countries in Highest and Lowest difference in Fixed Average Upload Speed between 2019 Quarter 1 and 2021 Quarter 4

Ranking	Country	Latency(ms)
1	South Sudan	-540.69
2	Antarctica	-405.12
3	Eritrea	-395.0
4	Solomon Islands	-371.04
5	Wallis and Futuna	-290.33
6	Yemen	-190.21
7	Tonga	-130.31
8	Niger	-114.5
9	Venezuela	-103.85
10	Equatorial Guinea	-96.29

(a) Top 10 Countries with Highest Decrease in fixed Average Latency (improvement)

Ranking	Country	Latency(ms)
1	Central African Republic	543.16
2	Nauru	469.56
3	Dem. Rep. of the Congo	181.15
4	Norfolk Island	157.25
5	Papua New Guinea	90.64
6	Niue	75.5
7	Vanuatu	38.87
8	Chad	32.42
9	Comoros	30.35
10	Zambia	23.08

(b) Top 10 Countries with Highest Increase in fixed Average Latency

Table 7: Top 10 countries in Highest Decrease and Highest Increase in Fixed Average Latency Speed between 2019 Quarter 1 and 2021 Quarter 4

A.2.2 Mobile Tiles

Ranking	Country	Speed(mbps)
1	United Arab Emirates	339.26
2	Cyprus No Mans Area	252.58
3	China	228.08
4	Cyprus	204.57
5	South Korea	185.76
6	Kuwait	147.79
7	Saudi Arabia	134.55
8	Qatar	131.86
9	Bulgaria	127.24
10	Bhutan	106.84

(a) Top 10 Countries with Highest Growth in mobile Average Download Speed

Ranking	Country	Speed(mbps)
1	Djibouti	-24.74
2	Samoa	-22.23
3	Comoros	-18.34
4	Cook Islands	-13.35
5	Montenegro	-12.94
6	Lebanon	-8.92
7	San Marino	-8.79
8	New Caledonia	-4.59
9	Sri Lanka	-4.51
10	Equatorial Guinea	-3.52

(b) Top 10 Countries with Highest Decline in mobile Average Download Speed

Table 8: Top 10 countries in Highest and Lowest difference in Mobile Average Download Speed between 2019 Quarter 1 and 2021 Quarter 4

Ranking	Country	Speed(mbps)
1	China	35.76
2	United Arab Emirates	30.64
3	Iraq	20.79
4	Dhekelia Sov. Base Area	19.95
5	Brunei	18.92
6	Cyprus	17.03
7	Cyprus No Mans Area	16.51
8	Suriname	14.63
9	Qatar	14.46
10	Bosnia and Herzegovina	14.19

(a) Top 10 Countries with Highest Growth in mobile Average Upload Speed

Ranking	Country	Speed(mbps)
1	Comoros	-7.57
2	Djibouti	-7.51
3	Samoa	-5.48
4	Gambia	-5.01
5	Belize	-3.96
6	Barbados	-3.93
7	Cook Islands	-2.85
8	New Caledonia	-2.78
9	Fed. States of Micronesia	-2.73
10	East Timor	-2.48

(b) Top 10 Countries with Highest Decline in mobile Average Upload Speed

Table 9: Top 10 countries in Highest and Lowest difference in Mobile Average Upload Speed between 2019 Quarter 1 and 2021 Quarter 4

Ranking	Country	Latency(ms)
1	Nauru	-238.86
2	American Samoa	-234.82
3	South Sudan	-214.04
4	Niger	-185.99
5	Sao Tome and Principe	-163.49
6	Somalia	-156.13
7	Yemen	-114.43
8	Gibraltar	-112.75
9	Chad	-97.70
10	Fed. States of Micronesia	-81.49

(a) Top 10 Countries with Highest Decrease in mobile Average Latency (improvement)

Ranking	Country	Latency(ms)
1	Comoros	103.63
2	Greenland	103.22
3	British Virgin Islands	21.64
4	Djibouti	20.48
5	Togo	18.41
6	Saint Kitts and Nevis	17.47
7	Colombia	12.13
8	Central African Republic	9.98
9	Dhekelia Sov. Base Area	8.28
10	Cook Islands	6.88

(b) Top 10 Countries with Highest Increase in mobile Average Latency

Table 10: Top 10 countries in Highest Decrease and Highest Increase in Mobile Average Latency Speed between 2019 Quarter 1 and 2021 Quarter 4