Visualizing Internet Measurements of Covid-19 Work-from-Home

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***Abstract*—The Covid-19 pandemic disrupted the world as businesses and schools shifted to work-from-home (WFH), and comprehensive maps have helped visualize how those policies changed over time and in different places. We recently developed algorithms that infer the onset of WFH based on changes in observed Internet usage. Measurements of WFH are important to evaluate how effectively policies are implemented and followed, or to confirm policies in countries with less transparent journalism. This paper describes a web-based visualization system for measurements of Covid-19-induced WFH. We build on a web-based world map, showing a geographic grid of observations about WFH. We extend typical map interaction (zoom and pan, plus animation over time) with two new forms of pop-up information that allow users to drill-down to investigate our underlying data. We use sparklines to show changes over the first 6 months of 2020 for a given location, supporting identification and navigation to hot spots. Alternatively, users can report particular networks (Internet Service Providers) that show WFH on a given day. We show that these tools help us relate our observations to news reports of Covid-19-induced changes and, in some cases, lockdowns due to other causes. Our visualization is publicly available at https://covid.ant.isi.edu, as is our underlying data.**

***Index Terms*—Covid-19, work-from-home, visualization, drill-down, SQL.**

I. Introduction

THE Covid-19 pandemic has drastically changed how we gather and interact with others, changing our social patterns, work habits, and interactions. Throughout 2020, health experts have suggested that social distancing and reduced face-to-face communication are necessary to control the virus [1]. Reflecting this advice, many governments and organizations have enacted work-from-home (WFH) recommendations or mandates [2]. Public and political reaction has been mixed, with some areas embracing work-from-home and others rejecting it [3]. Enforcement has also varied, with some instances of local officials refusing to implement statewide policy [4]. In other areas, "personal responsibility" has been emphasized, suggesting people should work-from-home (or not) at their discretion [5]. As a result it is challenging to know when work-from-home orders are actually followed, or to what extent people voluntarily choose to work from home.

Work-from-home using our home computers has induced changes in how we interact with the Internet, with wide adoption of new tools for work such as video conferencing and growth in home Internet [6].

We have developed algorithms that observe this shift through examining the changes in Internet usage. One can observe diurnal behaviors in the Internet as people go to work, go home, and sleep [7]. By observing networks with a noticeable diurnal trend that follows the typical work-week, we can infer work-from-home by the disappearance of that trend [8]. With new algorithms we are able to re-analyze our scans of the global Internet which we conduct regularly to detect Internet outages (from Trinocular [9]), to detect the breakage of the diurnal pattern, and summarize the onset of work-from-home as it occurs around the world.

Although these algorithms can provide us valuable data covering much of the globe, with thousands of networks, it can become difficult to identify the trends in the raw data and verify these algorithms. Therefore, we need tools to help us search through the data and find meaningful changes within millions of records at various times and locations around the world. Understanding this data is critical to validate true positives in participation in work-from-home, where the data shows the onset of work-from-home corresponding with official policy. Validation can also help us detect surprising true negatives—when work-from-home orders were met with the lack of actual implementation.

The contribution of this paper is a new system that visualizes work-from-home data on an interactive world map, along with drill-down methods to help investigate when, how much, and where networks changed. Our basic visualization (see Section II-A) utilizes OpenStreetMap to show work-from-home changes on a 2×2 degree latitude/longitude grid on a world map (Section III-B). This website provides geographic context for WFH changes, and with zoom and pan for animation, a user can quickly browse global data. We support user-interaction and "drill-down" into the underlying data through two new forms of pop-up information. We use sparklines to show changes over the first 6 months of 2020 for a given location, supporting identification and navigation to hot spots (Section III-E). Alternatively, users can report particular networks (Internet Service Providers) that show WFH changes on a given day (Section III-F). Finally, we provide several case studies that demonstrate how these tools help us relate our observations to news reports of Covid-19-induced changes and, in some cases, lockdowns due to other causes (Section IV). Our website is publicly available at https://covid.ant.isi.edu/.

II. Background and Related Work

A. Map Visualization

Web-based maps have evolved since around 2000, and have taken off since the 2005 introduction of Google Maps and tiled maps.

We extend the University of Southern California/Information Sciences Institute's Internet Outage World Map [10], which in turn is built on OpenStreetMap's data and their slippy map implementation [11]. OpenStreetMap provides us a map framework, API, and tiles. The Outage World Map locates Internet outages [9], mapping IPv4 /24 blocks into grid cells of different resolutions (0.5, 1, or 2 degree latitude/longitude). Each grid cell shows a colored circle, unless there is no shift from the diurnal trend at that timestamp, with the area of the circle representing the number of IPv4 blocks that are out in that region, and the color of the circle showing the fraction of blocks that are out. In this paper, we replace outage data with Covid-WFH data and add new methods for interaction with drill-down (Section III).

B. Detecting Covid-19 Work-From-Home

Our Covid-19 Work-from-Home visualization uses data from our Covid-WFH algorithm [8]. We summarize the four steps of the algorithm here: (1) data collection, (2) identifying *change-sensitive* blocks, (3) de-trending, and (4) change detection.

The input to Covid-WFH detection are ICMP echo requests ("pings") that cover as much of the public, unicast IPv4 network as possible. We use the data from Trinocular [9, 12], covering about 5M /24 IPv4 address blocks (as of 2021) with new data arriving for each block every 11 minutes. While active probing cannot see behind network-address translation and firewalls, Trinocular [9], with improvements [12], provides quite accurate outage detection.

Covid-WFH detection *reinterprets* this raw data, aggregate multiple observers and accumulate it over time to estimate the current state of each address (not just outages).

Next, we identify *change-sensitive blocks* in this data. A block is considered to be change-sensitive if we observe regular daily changes in it (that is, it shows a diurnal pattern [7]), and if those changes are large enough that we believe we can tell when they change. All in all, we detect approximately 447k change-sensitive blocks.

We then look for *trends* in this data. The daily and weekly fluctuations may blur the long-term changes in usage so we employ Seasonal-Trend decomposition using LOESS model [13] for extracting the baseline diurnal-use signal from the data.

Finally, we look for *downward changes* in the trend of change-sensitive blocks. A downward trend indicates a drop in the number of daily users of that block, after we filter out the daily and weekly trends. We apply CUSUM, a change-point detection algorithm, to the baseline for detecting the specific point when the decline begins. Our assumption is that this point will capture the start of work-from-home trend, because it indicates that the work-day induced diurnal pattern becomes suddenly less prominent or even disappears. The evaluation of accuracy of randomly selected locations shows the large number of WFH detections on dates that correspond to news reports about the country starting lockdown.

C. Other Studies of Covid-19 and the Internet

Covid-19 led to an increase in Internet traffic as many workplaces switched to an at-home, virtual setting, and people's social lives moved on-line. Facebook reported an increase in traffic [14]. Feldmann et al. observed and evaluated how the Internet reacted at several European ISPs and Internet Exchange Points [15]. While these papers studied how Covid-19 affected Internet use, we instead visualize the changes in Internet indicative of the public's response to Covid-19.

More closely related to our work, researchers from Telefonica examined data from mobile telephones to evaluate data usage, user mobility, and response to work-from-home [16]. They are able to identify the location and mobility pattern of specific users from mobile phone identities and GPS, information available only to mobile network operators. Visualizing user location only in general ways, Telefonica researchers evaluate the amount of mobility per day and group users by city. In contrast, our work uses information gathered from a third-party location (pings of public IP addresses). Since we do not possess individual user identities and therefore cannot evaluate per-user mobility, we choose to report changes by region.

D. Other Visualizations of Covid-19

Multiple groups visualize Covid-19 information at the county, state, or national level [17, 18, 19]. Typically, they are visualizing data from public health reports (displaying number of Covid-19 cases in an area, etc.). The way in which these groups display the data varies, using heat maps, line graphs, scatter graphs, etc. Additionally, some of these sites support interactive geographic drill-down, zooming in on states to show counties.

Our work instead uses data inferred from measurements of the Internet on a global scale. It is therefore independent of public health records. Strong public health data can be very powerful, including factors such as race and ethnicity that we cannot measure. However, our independent source of data can provide insight into countries or regions that lack public health data, or that decline to publish it [20]. In addition, our visualization allows users to drill-down into the underlying data through timeseries graphs and tables.

III. Methodology: Visualization to Make the Data Useful

A. Problem Statement

Our goal is to support human interaction with our Covid-19 work-from-home findings. We begin with our Covid-WFH data in a database. While SQL supports sophisticated users with tabular output, it cannot accommodate a casual user or provide geographic context. Our goal is to support both casual and sophisticated users to answer different questions that often benefit from geographic context.

Where (geographically) do events happen? Our first goal is to determine *where* events, each a real-world change in Internet usage, occur. Generally, Covid-WFH mandates are enacted by governments and affect their local jurisdiction. To display this

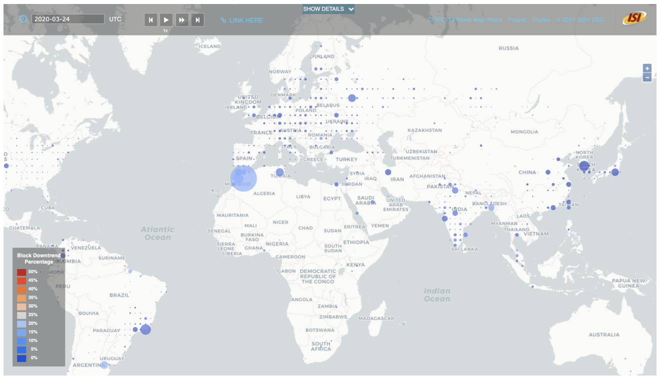

Fig. 1. Grid cells at 2-degree resolution containing Covid-WFH downtrends.

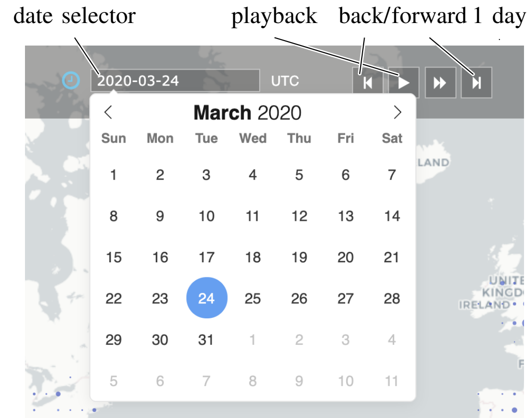

Fig. 2. Details of date selector and playback buttons on 2020-03-24.

information, we create a world map, allowing users to identify these jurisdictions.

When do events happen? Once we know where an event occurs, the subsequent question is when. Understanding the timing of an event requires tools to navigate to different dates and view global changes over time.

In addition, we want to understand the *intersection* of geography and time. How does a *particular location* change over time? Or what about several locations in a region?

Why do events happen? Given an event at a specific location and date, we would then like to know why it happens there, and what specific changes occurred. To validate "why" is outside the scope our data—it requires consulting media and government documentation of policy changes.

B. Map-based Visualization: Where do events happen?

To place the Covid-WFH geographically, we begin by displaying the data on a world map, as shown in Figure 1. We divide the world up into geographic grids of 0.5-, 1-, or 2-degree latitude/longitude cells, switching to a finer resolution with a smaller grid size as the user zooms in. Internet networks are unevenly spread around the globe, correlating with the population density. The grid allows for a roughly uniform geographic coverage, and it is easy to map to a database, unlike alternatives that dynamically place variable numbers of map markers.

Each grid cell shows a circle representing the downward trend in Covid-WFH for that cell on that day. The area of the circle is in proportion to the number of networks showing Covid-WFH fluctuations on that day—in Figure 1 we see very large numbers of networks (large circles) in South Korea and China, and more uniform networks across most of Europe. The color shows the *fraction* of networks that change. In Figure 1 all circles are dark or medium blue, showing 0-15% of networks in each region demonstrate a downward trend in diurnal signal.

Finally, our map supports user interaction in several ways. Users can pan and zoom, and clicking on a grid cell renders drill-down to provide additional information on that location as described below in Section III-D.

C. Time Travel: When do events happen?

Covid-19 affected different parts of the world at different times, so we support temporal browsing in two ways.

First, the overall map has both a date and time selector for the user to select which day to display across the whole map as shown in Figure 2. (Currently we display the first 6 months of 2020.) We also have previous and forward buttons that jump by one day in either direction. We find that this combination allows users to quickly transition to a date of interest (with the date selector), or to browse around a given date (with arrows).

We also support automatic playback—the user can select the "playback" button and the map will automatically advance into the future. This animation can be paused and resumed, and the playback speed can also be set. We find that playback makes it easy to browse through a period of interest, watching for events, as we discuss in Section IV-A.

Temporal browsing integrates well with the world map—the user can select a geographic area of interest and then browse through time, or play back a large part of the globe and then zoom in on areas of interest.

D. Prioritizing Information with Drill-down

While the world map provides a "big picture," we need more details to investigate specific events. We use drill-down to annotate the world map with information about specific locations.

When the user selects a specific event (a circle on a grid), we display a pop-up with more information about that area. This basic pop-up provides general information: the location's coordinates, the total number of IPv4 blocks that are change-sensitive at that location, the number of IPv4 blocks experiencing a downtrend on the current day, and the percentage of change-sensitive blocks that show a downtrend. Figure 3 shows this information for a location in China in March 2020.

This information provides a view of the quantitative data behind our visualization. The numeric values of numbers of blocks help evaluate when large changes are meaningful compared to large shifts that happen because of changes to a few blocks in a very sparsely populated area. In addition, the latitude/longitude coordinates can be useful for manual queries

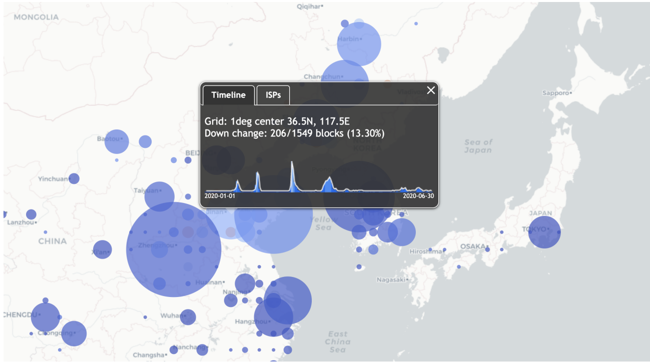

Fig. 3. A drill-down pop-up showing basic information with a sparkline (Section III-D). Shown here: the Laiwu District, Laiwu, Shandong, China on 2020-03-11.

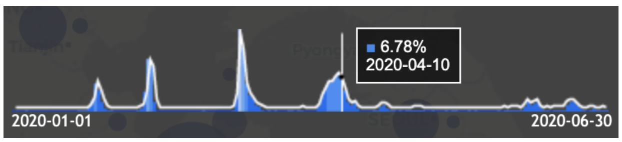

Fig. 4. Details of the sparkline for Laiwu District, Laiwu, Shandong, China from Figure 3.

in SQL by expert users. Finally, to answer other questions in the UI, we augment this basic information with sparklines and ISP tables as described next.

E. Drill-down with Temporal Sparklines: When do events happen at a specific location?

While animations and temporal browsing (Section III-C) allow one to scan a region of the globe for changes over time, the screen shows only one day at a time.

Complementing this view, we also support temporal sparklines to show how a particular location changes over time. A sparkline is shown at the bottom of the pop-up in Figure 3; we show only the sparkline in Figure 4. The sparkline shows 6 months of data across the x-axis, with the height of the line showing the percentage of change-sensitive blocks experiencing a downtrend on each day for that location. To emphasize peaks, we color the vertical stripes for each day based on that day's percentage using the the same color scale as the circles on the world map.

By showing the timeline, the sparkline makes it easy to identify days with large downtrends.

A common discovery process is to scan the map for changes with animation playback, look at a specific hot spot in the sparkline to find the most prominent events for that location, and then shift the world map to the time of those events to understand context around the location. To support this process, our sparklines are interactive—a user can hover their mouse over the sparkline to see numeric values for a given date, and clicking on the sparkline causes the world map to jump to the target date. This process can be viewed in Section IV-B.

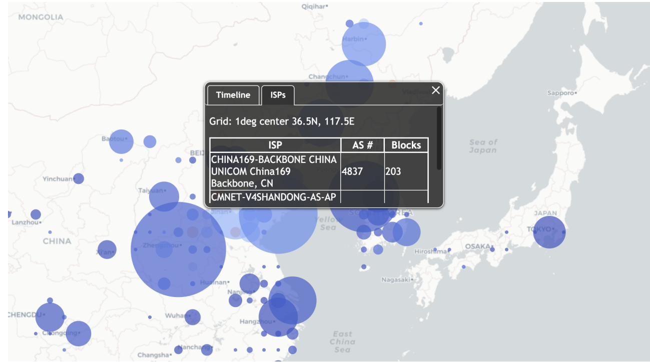

Fig. 5. An example of the pop-up's second tab which is rendered when the user selects Laiwu District, Laiwu, Shandong, China on 2020-03-11 (Section III-F).

F. Drill-down for ISPs: Why do events happen?

With support for where events happen (Section III-B) and when (Section III-C and Section III-E), we finally turn to *why*. To answer this question, we compare the date and location with external news sources. To assist in this process, our second drill-down mode provides information about the ISPs that change on a given day. ISP names can help identify the nature of the networks that show changes in Internet use: residential, government, universities, or commercial workplaces.

Figure 5 shows ISP-based information in Laiwu, China in March 2020. We show each ISP name, the Autonomous System number, and the number of blocks in that organization that change on that day. These dynamic ISP tables can also lead to interesting discoveries, such as in Section IV-C.

G. Implementation Details

We next summarize specific implementation challenges we encountered and choices that had a positive effect.

Database storage: We store all underlying data in a database, organized in three pre-computed grid resolutions. Since we have only one data point per day per location, and only about 4000 locations on the globe are ever active, with an average 630 active location per day, this data is relatively small (114,291 records for 6 months). So searches are fast, and MySQL provides a good abstraction to extract the data in different ways (across the world on one day for the world map, or across all days for one location for the sparkline).

To keep the main database tables small, we normalize ISP information in a separate table, joining a list of downtrend blocks against ISP metadata on-the-fly to support ISP drill-down.

Screen size: We use a pop-up to keep drill-down information in context. However, pop-ups use only a fraction of the screen. To reduce the amount of space taken up by the pop-ups, we implement tabs to grant the user the option of transitioning back and forth between the data, as seen in Figure 3. By doing so, the user can view changes on the map while simultaneously examining a detailed break-down at a specific location.

Grid cells can have very different numbers of change-sensitive blocks, from a handful in rural areas to thousands in cells that contain large cities. As a result, information in the

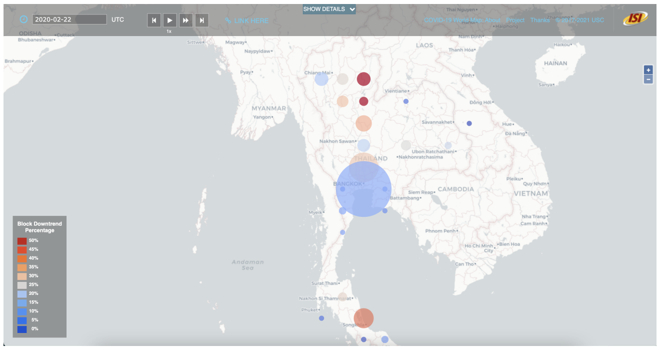

Fig. 6. Cluster of downtrends in Thailand on 2020-02-22, discovered using the play button located in the navigation bar (see Section IV-A).

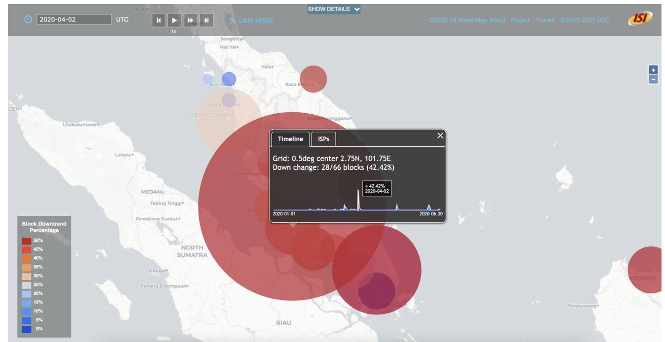

Fig. 7. Widespread downtrend in Malaysia on 2020-04-02 discovered using the interactive sparkline (see Section IV-B).

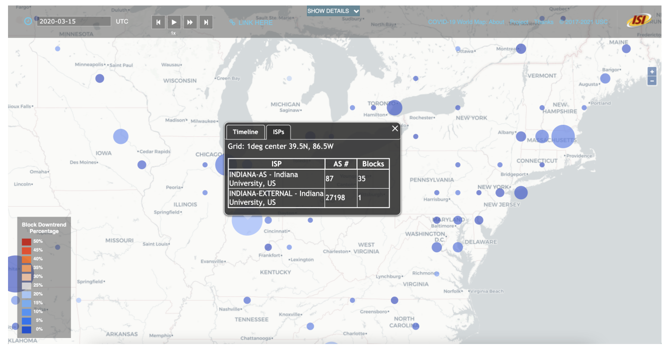

Fig. 8. Discovered using the ISP drill-down tables, central Indiana experienced its largest downtrend on 2020-03-15 due to Indiana University ending classes for spring break (see Section IV-C).

ISP drill-down can range from a few to hundreds of lines. We group blocks by ISP (eliminating specific IP address ranges) and add a scroll bar on the second tab for the user to browse the data.

IV. Evaluation: Discovering New Events and Causes

To evaluate our work we next examine several events discovered using our enhanced visualization system. These events complement the ones we have previously documented when developing the algorithms [8], and they illustrate the benefits of our various exploration methods provided by our visualization.

A. Playback Button: Discovery in Thailand

We first look at how the overall world map and playback assists in discovery. Playing out 2020 data through the animation while watching Asia, shows a "hot spot" in Thailand at the end of February. We then zoom in on the location, jump backwards in time, and play the data out more slowly, examining unique events in Thailand.

Figure 6 shows a snapshot of what we found on 2020-02-22. News reported that multiple institutions experienced disruptions from student-led protests in response to the Thai government's decision to disband the opposition party on this day [21].

Although this event was not due to Covid-19, it was captured due to a real reduction in Internet usage as shown in our data. Without our world map and animation, we would not have discovered this prominent event.

B. Sparkline: Discovery in Malaysia

Next, we demonstrate the utility of the interactive sparklines. While examining a change in Malaysia, we notice a large red spike in the middle of the sparkline. Hovering over the pop-up shows the change occurs on 2020-04-02, and clicking on that peak shifts the world map to that date, allowing us to closely examine the event, as seen in Figure 7.

According to media reports, Malaysia hit a record high of Covid-19 cases on 2020-04-02 and increased lockdown restrictions on that day leading to an increase in Covid-19 work-from-home [22].

Unlike Thailand, this event was a result of shifts to work-from-home due to Covid-19. While this event was in the underlying data we had processed, the sparkline made it very quick to find and navigate to the correct date.

C. ISP Drill-down: Discovery in Indiana

Finally, we were exploring downtrends in the United States in mid-March 2020, during early Covid-19 reactions, when we observed a moderate-size circle in Indiana and wanted to investigate why.

We turned to ISP drill-down. With the time selector, we see a large downtrend on 2020-03-15. The ISP drill-down shows that all the networks involved belong to Indiana University, as shown in Figure 8.

Prompted by this information we searched for news reports about Indiana University on this date. University websites and local news reported that Indiana University ended classes for spring break, and that they continued with remote classes following break due to Covid-19 [23].

This example shows that the network information can help bridge the gap between basic network observations, seen geographically, and logical locations (like a university), and that this link can help associate what we see with ground truth. In this case, the event began with a regular spring break and followed on with Covid-19-driven work-from-home.

D. Unintended Discoveries

Greater visibility into our data also helped us improve confidence in our system and detect inconsistencies. The ability to easily view the numeric values in our visual display assisted in confirming when red circles were real and backed by significant amounts of data, and when they reflected large changes in percentages based on random movement of a few blocks in rural areas.

We also discovered a comparison between different forms of drill-down and different zoom resolutions to be helpful. In some cases we found inconsistencies in the absolute number of blocks showing a downtrend on the first tab with the count of blocks listed on the ISP drill-down. We traced these discrepancies to an inconsistent handling of SQL queries in our code.

V. Conclusions

This paper described our new website https://covid.ant.isi.edu to visualize Covid-19 Work-from-Home detection based on changes in Internet usage. We built on our prior work visualizing Internet outages with OpenStreetMap's slippy map. We added Covid-19-WFH detections to this map, and extended it with interactive drill-down. We showed the importance of the map to quickly scan large amounts of data, of sparklines to show changes in Covid-19-WFH over time at a specific location, and ISP-reporting to indicate which ISPs are reflected in this data. We used these tools to discover several events in our data, some related to political protests that caused real Internet shutdowns but not Covid-19-related, as well as several events that we tied to Covid-19-WFH changes. We hope this interactivity will be useful to similar kinds of data visualization in the future, and look forward to visualizing Covid-19-based return-to-work events as part of our future work.

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