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EXTENDED ABSTRACT

Real-Time Mobility Analysis Through Google Maps

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Policy Significance Statement
We show how real-time, up-to-the-hour data on visits to popular locations on Google Maps can be collected, visualized and analyzed to support monitoring of stay-at-home recommendations, as well as to support fine-grained estimates of economic impact. A dashboard built for this data is being used by the Qatari Ministry of Public Health.

Extended Abstract

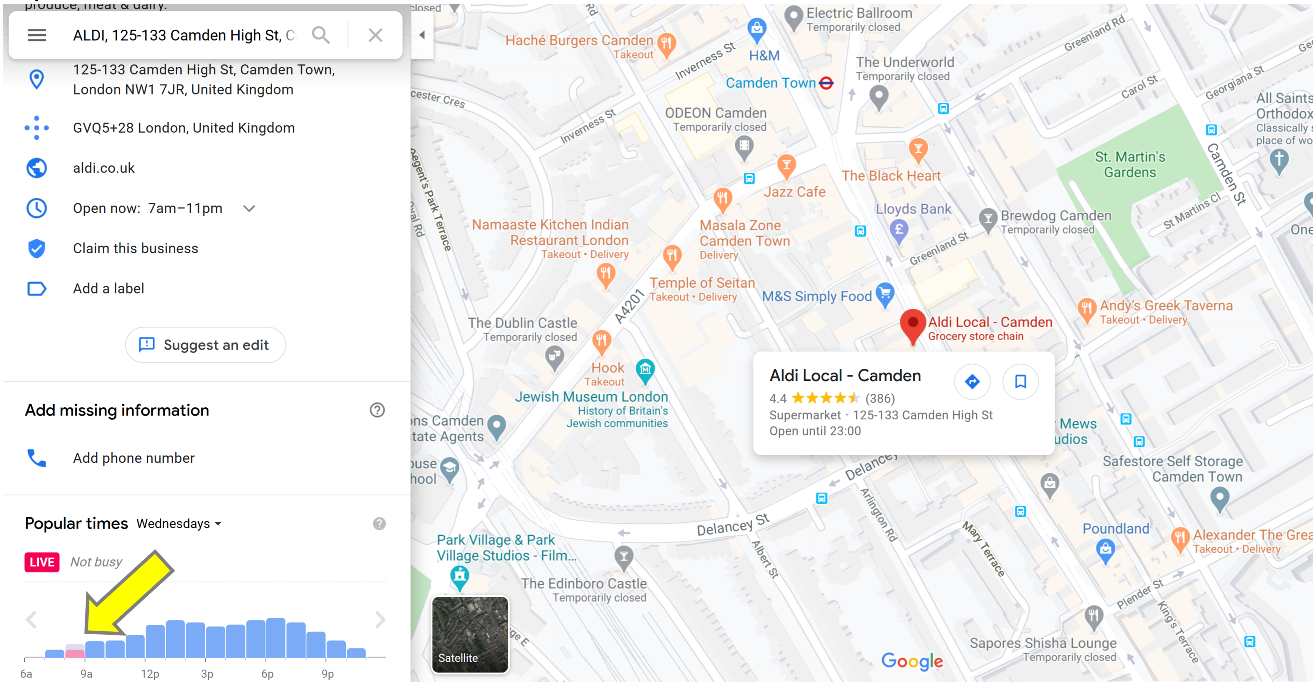
The spread of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) and the associated coronavirus disease 2019 (COVID-19) has lead to at least 315k confirmed deaths [1] around the globe, with many more likely not being counted. To rein in the spread of the virus, most countries resort to enforcing "social distancing" through different forms of lock-downs and stay-at-home orders. These necessary efforts have led to negative economic consequences not seen since the Second World War[2].

To minimize the loss of life, as well as the negative economic impact, governments need real-time measures of how well current restrictions are being observed. Having spatially fine-grain and real-time data on this, ideally combined with fast and wide-spread testing for the virus, could support governments in fine-tuning their response without being too lax or drastic in their measures. In this extended abstract, we present our ongoing efforts in collecting, visualizing and analyzing publicly available real-time data about location visits through Google Maps to provide public health officials with insights into visit patterns to certain locations.

Google Maps[3] provides information about "popular times"[4] for certain locations. Figure 1 shows a screenshot with this information for an ALDI supermarket in Camden Town, London. The blue histogram on the left shows the typical visit patterns for a Wednesday with expected peaks between 1-2pm and 6-7pm. Furthermore, it shows the current live traffic in pink for the current hour of 8-9am (the time when the screenshot was taken). Both the typical, historic baselines and the at-this-hour values, can be obtained programmatically through an Application Program Interface (API)[5]. The API returns normalized values with the highest typical hour corresponding to a value of 100 and other values normalized with respect to this value. The historic reference values "are based on average popularity over the last few months"[2].

[1] https://coronavirus.jhu.edu/data, as of June 20, 2020.
[2] https://www.nytimes.com/2020/04/30/business/europe-economy-coronavirus-recession.html
[3] https://maps.google.com
[4] https://support.google.com/business/answer/6263531
[5] The data for this particular location can be obtained as JSON through https://tinyurl.com/AldiCamdenLiveInfo.

Figure 1. Screenshot of Google Maps, showing the live visit information for an ALDI supermarket in Camden Town, London, on the left. The normalized, typical visit volume on a Wednesday between 8-9am has a value of 18 (out of 100). The current value around 8am local time on Wednesday, May 13, was 10 (out of 100). All values are normalized with respect to the maximum traffic, typically observed on Mondays 6-7pm (value of 100 – not shown). .



As far as we know, there is no prior work that uses the as-of-this-hour live estimates provided by Google in any context. However, other researchers have used the historic estimates for the "popular times". In particular it has been used to model traffic flows and CO2 consumption Tafidis et al. (2017); Bandeira et al. (2020), to predict demand for charging of electric vehicles Dixon et al. (2020), and to predict building occupancy Lu et al. (2019); Happle et al. (2020); Toepke (2017), in particular with the goal of predicting a building's current energy consumption Yoshida and Yamagata (2020); Yoshida et al. (2019).

We have so far built 15 dashboards around this data, covering locations from Marrakesh, to Guadalajara, to Qatar. Figure 2 shows a screenshot of the dashboard for Milan, Italy. For the chosen selection, locations are color-coded according to their (observed on May 12)/(expected on a typical Tuesday) estimates with red locations indicating more visits than expected and dark green indicating no more than 40% of the reference values. Selections can also be made for different location types such as only supermarkets or petrol stations.

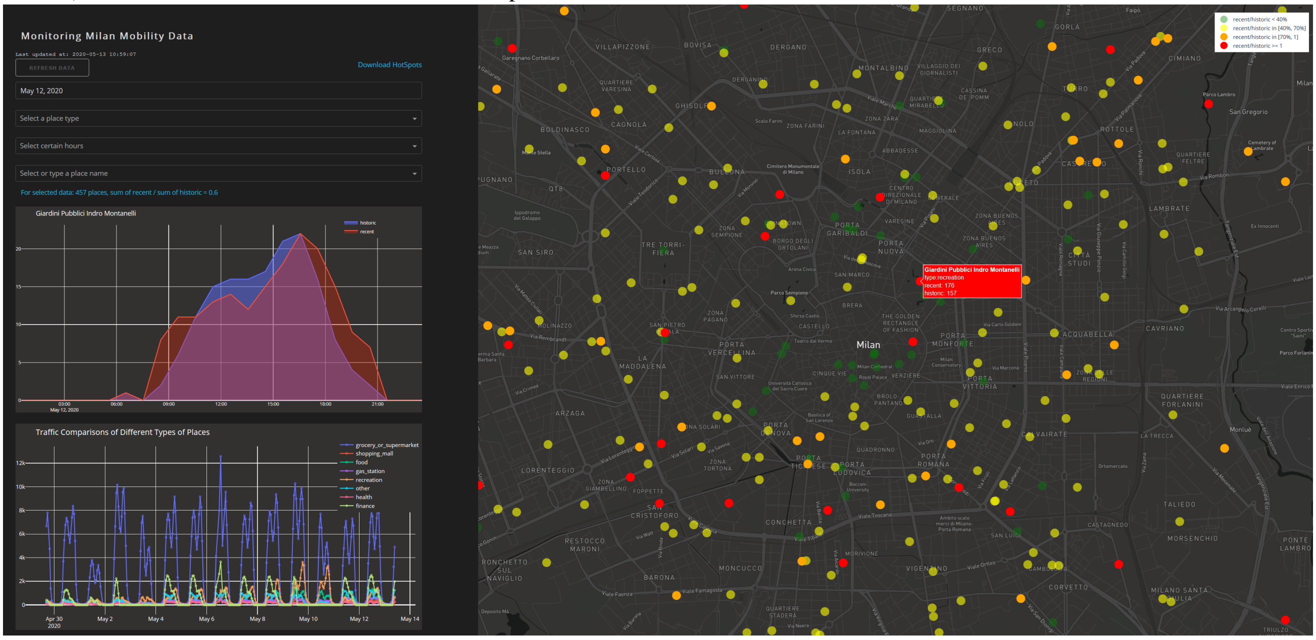
A version of such a dashboard showing live information for over 500 locations in Qatar is currently being used by the Ministry of Public Health (MoPH) to observe where social distancing might not be observed. An example of a concrete insight derived from this data includes an increase of visits, compared to the historic baseline, to petrol stations in Qatar around 2am. These visits seem to correspond to visits to small convenience stores at petrol stations, providing an example of how people have adjusted their shopping behavior due to covid-19.

Beyond applications for public health surveillance, we are also exploring if a similar analysis could be used to estimate spatially fine-grained economic recovery as countries start to relax their lock-downs. In particular the World Bank has expressed interest in exploring the use of such data for now-casting economic activity.

Note that coarse-grained reports about visit patterns are also provided by Google itself through their Covid-19 Community Mobility Reports[6]. These reports, though useful, lack in (i) sub-city disaggregation, with the smallest unit being a state for large enough countries, as well as in (ii) real-time availability, with a 3-4 day lag between the release date and the last day covered, and reports being only

[6] https://www.google.com/covid19/mobility/

Figure 2. Screenshot of data vizualization for Milan, Italy. On the right, each dot represents one of the 457 locations for which live visit information was collected on Tuesday, May 12, 2020. On the left, detailed information for the selected location, the public gardens "Giardini Pubblici Indro Montanelli" is shown. For that day, the sum of live/recent information, shown in red, was 176, whereas the sum of normalized typical visit information, shown in blue, is 157. Across all the 457 locations with live information on that day the (sum of recent)/(sum of historic) is 0.6, shown on the left below the selection options. .



released roughly once a week. Though our approach lacks in completeness of its coverage, as it only includes fairly popular locations, it does afford the benefits of POI-level up-to-the-hour information.

Relying on digital traces, however, also comes with the risk of bias and of "leaving people behind" by not includind them. At this point we do not yet know enough about the kind of users opting-in to share location information with Google and who is under- or over-represented. Similarly, there are related biases in the locations that attract sufficient visits for Google to provide anonymous, real-time information. Such information is not available for smaller, neighborhood corner stores. Despite these limitations we still believe that this data source could help to create real-time situational awareness during the Covid-19 pandemic.

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