Multiscale Dynamic Human Mobility Flow Dataset in the U.S. during the COVID-19 Epidemic

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Abstract

Understanding dynamic human mobility changes and spatial interaction patterns at different geographic scales is crucial for monitoring and measuring the impacts of non-pharmaceutical interventions (such as stay-at-home orders) during the pandemic. In this data descriptor, we introduce a multiscale dynamic human mobility flow dataset across the United States, with data starting from March 1st, 2020. By analysing millions of anonymous mobile phone users’ visit trajectories to various places, the daily and weekly dynamic origin-to-destination (O-D) population flows are computed, aggregated, and inferred at three geographic scales: census tract, county, and state. There is high correlation between our mobility flow dataset and openly available data sources, which shows the reliability of the produced data. Such a high spatiotemporal resolution human mobility flow dataset at different geographic scales over time may help monitor epidemic spreading dynamics, inform public health policy, and deepen our understanding of human behavior changes under the unprecedented public health crisis. The timely generated open data can support many other social sensing and transportation applications.

Background & Summary

The outbreak of the novel coronavirus disease SARS-CoV-2 (also known as COVID-19) in December 2019 has become a global threat to public health and human societies. Thus far, more than seven million people have been infected by the virus with more than four hundred thousand death cases globally [17]. To contain the transmission of the COVID-19 pandemic, social distancing has been proved as the most effective non-pharmaceutical intervention [20, 13], and governments have applied various policies to reduce human mobility, such as regional lockdowns [2], stay-at-home orders [20, 21], and travel restrictions [53, 56]. Tracking dynamic human mobility changes and spatial interaction patterns is therefore a prerequisite for measuring the effects of human mobility and interventions on predicting the virus spread [23, 13]. Several recent works have employed human movement O-D network-based epidemic models to project the numbers of COVID-19 infected population in China and Italy [24, 25, 26, 27, 28], which requires timely updated inbound and outbound human movement flow information. However, there is no such openly and timely updated human movement O-D flow matrix data at a fine spatiotemporal resolution available in many other countries where researchers can only use historical O-D survey data and other proxies as a compromise [33].

Human mobility has been widely studied in multiple disciplines such as geography, urban planning, physics, computer sciences, and public health [10]. It reflects patterns about how people move from place to place and serves as an indicator of human behaviour and underlying socioeconomic environments. With the rapid development of information and communication technologies (ICT) and GPS embedded devices, large-scale mobile phone data provides an unprecedented opportunity in tracking human trajectories, which benefits research about human mobility patterns. Existing studies have used such data to investigate basic laws governing human movements [24, 13], model regional transportation connectedness and economy [30, 12], describe daily commuting flows [27], compute urban vibrancy [30, 49], inform public health policy [35, 37, 31], and understand spatial interaction patterns [19, 11, 14].

As pointed out by [20, 13, 32], human mobility data plays a key role and serves as data foundation in the fight against the COVID-19 epidemic. Although companies such as Descartes Labs [31], Apple [1], Google [3], Facebook [33], etc., have released a set of near real-time mobility-related open datasets for monitoring human mobility changes and social distancing behaviors during the COVID-19 period, these datasets are lacking in three respects. First, human mobility flow matrices, which describe movement patterns from origin geographic units to destination regions, are often unavailable, even though such origin-to-destination (O-D) paired flow data are incredibly valuable for epidemic transmission modeling and social distancing measurements [35, 15, 52, 6]. For instance, only aggregated mobility indices (such as median travel distance and foot-traffic) at a specific region is provided by the Descartes Labs, Apple, and Google mobility datasets. Second, there is a lack of fine-resolution datasets regarding the privacy-accuracy trade off. Third, the mobile phone or other sensor data-driven mobility patterns often only provide a sample (e.g., 10%) of the entire population. There is no entire-population-level estimated flow data. To address the limitations of existing mobility databases, we introduce an openly available dataset that provides an estimation of dynamic population flows at multiple spatial scales (at the census tract, county, and...
state) and temporal resolutions (daily and weekly) across U.S. during the COVID-19 epidemic considering the findability, accessibility, interoperability, and reusability of data [22]. The O-D format dataset is generated by tracking millions of anonymous visitor trajectories collected by SafeGraph [12]. When producing the dataset, great effort was taken to protect personal privacy by aggregating to various geographic scales so that individual information cannot be traced. Other public datasets, such as the the American Community Survey (ACS) commuting flows and the Descartes Lab COVID-19 mobility dataset are then compared to illustrate the reliability of the produced dataset. Such a near real-time dataset can be a useful supplement in human mobility observation. It can be used not only for fighting against the global pandemic, but also to benefit other research and applications such as emergency response [21, 23], urban planning [11], and population migration [29].

Methods

Figure 1 illustrates detailed processing steps for how our human mobility flow dataset is generated. The dynamic population O-D flows are estimated using mobile phone location data provided by SafeGraph and demographic data retrieved from the American Community Survey (ACS). Based on millions of anonymous mobile phone user visits to various places tracked by SafeGraph, two types of visitor flows, namely daily census block group (CBG) to CBG visitors and weekly CBG to point of interest (POI) visitors are computed, respectively. After spatially joining the place visitors to the administration regions, the visitor O-D flows are computed at three different spatial scales: census tract, county, and state, which are used to provide both micro and macro views of human mobility and spatial interactions patterns between different places. Since the number of mobile phone users detected by SafeGraph is only about 10% sample of the entire population [4], we further employ the ACS population data with mobile phone data samples to infer the population level of dynamic flows.

Track Place Visits

The place visitor patterns are retrieved from the SafeGraph COVID-19 Data Consortium [12]. By tracking millions of anonymous GPS pings from numerous mobile applications, individual user trajectories are identified, and thereby the home place of each user and visits to various points of interest (POIs) are detected. To protect privacy, home places are aggregated to census block groups (CBGs) where mobile users belong to, and no individual records can be traced and accessed.

POIs are the finest venue for tracking place foot-traffic by SafeGraph, while CBGs are one of the fine-resolution geographical units the United States Census Bureau used for publishing demographic and socioeconomic data. In total, there are more than 5 million POIs stored in the database, as well as more than 220 thousand CBGs retrieved from the ACS. The spatial distribution of POIs across the Contiguous United States is mapped in Figure 2 which shows that places cluster in major cities and are generally located along streets. The more places, the brighter the region in the map.

Compute Visitor Flows

Two major human mobility flow metrics are employed in data production, and are denoted as daily CBG to CBG visitor flows and weekly CBG to POI visitor flows. In the daily CBG to CBG visitor flows metric, each row contains an origin CBG and a destination CBG, as well as the amount of mobile phone-based visitor flows from the origin CBG to the destination CBG. Everyday, the number of unique mobile phone users who live in the origin CBG and stop at the destination CBG for at least 1 minute are recorded. Hence, the daily mobile phone-based visitor flows between CBG and CBG are grouped and summed up. A sample record of the daily CBG to CBG visitor flows included in Table 1. For the weekly CBG to POI visitor flows metric, different from the daily CBG to CBG visitor flows metric, which aggregates visitors between origin CBG and destination CBG directly. Weekly Patterns provides a mapping of CBGs to POIs. In other words, the number of unique visitors who live inside the origin CBG and visit the destination POI in one week are counted. A sample record of the weekly CBG to POI visitor flows included in Table 2.

Multiscale Aggregation

The two mobile phone-based visitor flows metrics (from CBG to CBG and from CBG to POI) are both processed at the CBG scale. After obtaining these two metrics, all data are further aggregated into three different spatial scales: census tract, county, and state. The motivation for providing data products at multiple spatial scales is discussed as follows. First, using coarser/finer analysis unit will lead to different outputs, which is known as the scale effect. As an important and fundamental concept in geography, the scale effect exists in almost all geographic phenomena [11], including human mobility patterns [10]. Providing a multiscale flow dataset allows us to have a more comprehensive view of human mobility and spatial interaction patterns. Second, various research projects may require data at different spatial scales, depending on the usage. For example, for research focusing on a macro view of spatial interactions, state or county scale data might be more suitable as it reflects general regional mobility patterns, while census tract scale data can be used for describing a micro view of human movement patterns such as within cities. Also, considering the data size-accuracy trade-off (i.e., the higher the spatial resolution, the higher the accuracy but the larger the data size is), providing a multiscale dataset enables users to download the data that fit their own needs. Third, although the daily CBG to CBG visitor flows and weekly CBG to POI visitor flows have been computed at the CBG scale, which is a finer spatial scale, aggregating them to upper-level can preserve the data privacy. Therefore, the mobility flow dataset is generated at three geographical scales respectively. To
do so, we assign census tract, county, and state’s geographically unique identifier to each origin CBG and
destination CBG that they belong to, and group all records according to the O-D pairs. In total, there are
74,001 census tracts, 3,219 counties, and 52 states (including Washington D.C. and Puerto Rico) at each
spatial scale for aggregation in the United States. The aggregated mobile phone-based weekly CBG to POI
visitor flows and the daily CBG to CBG visitor flows are termed as weekly visitor flows and the daily visitor
flows, respectively.

Infer Dynamic Population Flows
The abovementioned visitor flows at the three spatial scales are based on mobile phone users detected by
SafeGraph, not on the entire population. Such visitors only occupy about 10% to the entire population in
the U.S., and the sampling ratio of unique mobile devices to population vary across CBGs to CBGs [3].
Although existing studies have shown that 1% samples of the entire population can reflect general human
mobility patterns [24], we still aim to infer the real-world dynamic population-level flows as it is important
to accurately estimate meta-population infection cases and in other human mobility applications [25, 33].
To do so, by utilizing the official ACS population data with mobile phone visitor patterns, the dynamic
population flows are inferred using the following equation:

\[
pop_{\text{flows}}(o, d) = \text{visitor}_{\text{flows}}(o, d) \times \frac{\text{pop}(o)}{\text{num\_devices}(o)}
\]  

(1)

where \( \text{pop\_flows}(o, d) \) is the estimated dynamic population flows from geographic unit \( o \) to geographic unit
\( d \), \( \text{visitor\_flows}(o, d) \) is the computed mobile phone-based visitor flow from \( o \) to \( d \), \( \text{pop}(o) \) indicates the
population at the geographic unit \( o \) extracted from the ACS, and \( \text{num\_devices}(o) \) refers to the number of
unique mobile devices residing in \( o \). Note that we also conducted flow estimation experiments using a gravity
model [29] and a radiation model [30] but the goodness of fit results were varying across geographic scales.

Data Records
We have produced two data products: weekly flow data and daily flow data, both of which are provided at
the census tract, county, and state scales, starting from March 1st, 2020. All the data are available and will
be updated through an open data repository on Github: https://github.com/GeoDS/COVID19USFlows
Data provided in this repository are separated into two folders daily\_flows and weekly\_flows to store daily
flow data and weekly flow data, respectively. The two folders are organized according to the geographic
scale, where \( \text{ct2ct} \) indicates flows between census tract to census tract, \( \text{county2county} \) refers to flows between
county to county, and \( \text{state2state} \) contains flow data that originate from one state to others. All files are
stored in a comma-separated values (CSV) format, which has been widely used for storing, transferring,
and sharing data publicly. File names are formatted as \( \text{[data\_type]}_{\text{[spatial\_scale]}\_\{\text{date}\}\_\text{[csv]} \), e.g.,
daily\_ct2ct\_03\_02.csv and weekly\_state2state\_04\_19.csv. Specifically, for weekly flow data, the dates in
file name refers to the date of the Monday in that week but summarize all mobility flows in that week
from Monday to Sunday. Since the file size of flow data at the census tract scale exceeds the GitHub disk
limit, each flow data file is split into 20 subfiles (that can be merged after downloading). The daily and
weekly aggregated directional flows are coded by pairwise origin to destination units using geo-identifiers
(GEOIDs). The GEOIDs are numeric codes that uniquely identify different administrative levels (e.g.,
census tract, county, and state) in the U.S. Census Bureau data [4]. For the GEOIDs at each scale, census
tract is using an 11-digit number, county is a 5-digit number, and state is a 2-digit number. The
coordinates of origins and destinations can be used for creating spatial interaction flow maps. Reference
shapefiles at each scale are available from TIGER/Line Shapefiles https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html [5]. External demographic and socioeconomic statistical information at different spatial scales can be accessed directly from the U.S. Census Bureau and
joined to each origin and destination using GEOIDs [6]. A description of all attributes in the database is
shown below.

Weekly Flow Data
geo\_d - Unique identifier of the origin geographic unit (census tract, county, and state). Type: string.
geoid\_d - Unique identifier of the destination geographic unit (census tract, county, and state). Type: string.
lat\_d - Latitude of the geometric centroid of the origin unit. Type: float.
lng\_d - Longitude of the geometric centroid of the destination unit. Type: float.
date\_range - Date range of the records. Type: string.

visitor\_flows - Estimated number of visitors detected by SafeGraph between the two geographic units (from
geo\_o to geo\_d), computed and aggregated from weekly CBG to POI flows. Type: float.
pop\_flows - Estimated entire population flows between the two geographic units (from geo\_o to geo\_d),
inferred from visitor\_flows. Type: float.

Daily Flow Data
geo\_o - Unique identifier of the origin geographic unit (census tract, county, and state). Type: string.
geoid\_o - Unique identifier of the destination geographic unit (census tract, county, and state). Type: string.
lat\_o - Latitude of the geometric centroid of the origin unit. Type: float.
lng\_o - Longitude of the geometric centroid of the origin unit. Type: float.
during and after stay-at-home orders, which is an intuitive consequence of people reducing their movements captured. The total number of records before the stay-at-home orders is greater than the number of records between county to county as more types of flows (including not just the home-to-job commuting flow) are than the ACS commuting flow data. Our mobility flow dataset has a higher quantity of spatial interactions illustrated in Table 3. Regarding the number of records, the ACS commuting flows data contains 137,806 reflect the mobility patterns before, during, and after the stay-at-home orders, respectively. For daily flow by the COVID-19 epidemic. Due to the fact that a national emergency concerning the COVID-19 pandemic reflect the general patterns of commuting flows in the United States, i.e., normal mobility flows not affected fraction of regions, the comparison experiment is conducted only at county scale. The ACS commuting flows census tract and county scales. Noticing that only part of census tract scale data are covered in a small overall flow distributions are similar and keep consistent distributions (Figure 3B and 3C). The same was not true at census tract scale. Though most scatter points are distributed following the fitting line (R2 is 0.865 at census tract scale), those points with relatively high visitor flows and populations flows are located below the fitting line (Figure 3A). The reason is that most paired census tracts have only a few visits and scatter points aggregate near the coordinate origin. Therefore, the distributions of visitor flows and population flows keep consistency especially for those paired regions with a small number of visitor flows and population flows. In sum, it can be concluded that the computed mobile phone-based visitor flows and the inferred entire population flows have linear relationships even at different spatial scales. Since the overall flow distributions are similar and consistent across geographic scales, the population flows inference process is reliable.

Technical Validation

To check the data distribution and ensure the reliability of the produced mobility flow dataset, two complementary methods are employed for data validation. We first compare the probability distributions of the computed visitor flows and the estimated entire population flows to check if the data distributions stay consistent during the production process. Then, the released mobility flow dataset is compared with two other openly available data sources: ACS commuting flows and the Descartes Labs mobility changes. The hypothesis is that mobility patterns at the same geographic scale should be consistent across multiple data sources.

Checking Distributions of Visitor Flows and Population Flows

Following the methods described above, the two types (daily and weekly) of mobile phone-based visitor flows are directly aggregated at different geographic scales, while the demographic data are involved in estimating the entire population flows. Visitor flows and population flows are supposed to have similar distributions, and thus to make sure the inferring process keeps the distributions of the mobility flows unchanged, we made the Q-Q (quantile-quantile) plots to compare their distributions. Visitor flow and population flows are first normalized, as they have different value ranges. If the distributions of the two metric different compared are linearly related, the scatter points should locate following a line $y = kx$, where $x, y$ are percentiles of the two datasets and $k$ is the coefficient. Figure 3 shows the Q-Q plots of the visitor flows and population flows at three spatial scales based on the weekly flow data in the week of 03/02/2020 to 03/08/2020. Though we only plot the two distributions using one week data as an example, the associations between visitor flows and population flows are similar for other dates. As is shown in Figure 3 scatter points are distributed along a straight line at both county scale and state scale. Even though the line is not $y = x$, the inferred entire population flows are linearly related to the mobile phone-based visitor flows ($R^2$ is 0.958 at county scale and 0.953 at state scale and keep consistent distributions (Figure 3B and 3C). The same was not true at census tract scale. Though most scatter points are distributed following the fitting line ($R^2$ is 0.865 at census tract scale), those points with relatively high visitor flows and populations flows are located below the fitting line (Figure 3A). The reason is that most paired census tracts have only a few visits and scatter points aggregate near the coordinate origin. Therefore, the distributions of visitor flows and population flows keep consistency especially for those paired regions with a small number of visitor flows and population flows. In sum, it can be concluded that the computed mobile phone-based visitor flows and the inferred entire population flows have linear relationships even at different spatial scales. Since the overall flow distributions are similar and consistent across geographic scales, the population flows inference process is reliable.

Comparison with Other Data Sources

To illustrate that the data quality is high, we then compare two openly available data sources to the produced dataset from two different aspects, namely O-D flow patterns and temporal patterns. Correlation analysis is conducted to check if mobility patterns of the compared two datasets differ. Though there is no ground-truth data which characterizes the real dynamic population flows between two geographic regions as of yet, the comparison results are still useful for evaluating the credibility of the produced mobility flow dataset.

In terms of the O-D flow patterns between two regions, we take the ACS commuting flows as baseline to see if the mobility patterns before the pandemic detected in our data products have a high correlation with the ACS commuting flows patterns. ACS commuting flows are generated by asking participants about their residence locations and primary workplace locations, and such an O-D flow dataset informs the understanding of interconnectness between communities. ACS commuting flows provide data at both the census tract and county scales. Noticing that only part of census tract scale data are covered in a small fraction of regions, the comparison experiment is conducted only at county scale. The ACS commuting flows reflect the general patterns of commuting flows in the United States, i.e., normal mobility flows not affected by the COVID-19 epidemic. Due to the fact that a national emergency concerning the COVID-19 pandemic was declared on March 13, 2020, three time slices are picked up for comparison as they are supposed to reflect the mobility patterns before, during, and after the stay-at-home orders, respectively. For daily flow data, we chose March 2nd, April 6th, and May 11th as examples for comparison, while for weekly flow data we chose the weeks of March 2nd-5th, April 6th-12th, and May 11th-17th for comparison.

Comparison results between our produced mobility flow dataset and the ACS commuting flows data are illustrated in Table 4. Regarding the number of records, the ACS commuting flows data contains 137,506 rows, while the generated mobility flow dataset at the county scale contains more origin to destination pairs than the ACS commuting flow data. Our mobility flow dataset has a higher quantity of spatial interactions between county to county as more types of flows (including not just the home-to-job commuting flow) are captured. The total number of records before the stay-at-home orders is greater than the number of records during and after stay-at-home orders, which is an intuitive consequence of people reducing their movements

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during the pandemic. After joining the two datasets and removing records with no O-D matches, as is shown in Table 3, both weekly flow data and daily flow data had near perfect agreement (greater than 0.93) with the ACS commuting flow data. In particular, the inferred entire population flows have higher correlation coefficients with ACS commuting flows than the directly computed mobile phone-based visitor flows. With respect to the temporal changes, the flow patterns before stay-at-home orders have higher correlation coefficients, which matches expectations as people reduced their mobility when the stay-at-home orders in place, leading to a decrease in the correlation coefficient values.

Additionally, the temporal patterns of the introduced mobility flow dataset and the Descartes Lab’s COVID-19 mobility changes dataset is compared. Descartes Lab’s mobility changes dataset provides a mobility index which shows the median of the max-distance mobility of all users detected in one specific region. Such an index has been widely used for monitoring the daily mobility changes in the U.S. [26]. They are assumed to have similar temporal trends. To do so, the total number of mobile phone-based visitor flows and entire population flows in the daily mobility flow dataset and their mobility changes are matched in five U.S. metropolitan areas: New York, Los Angeles, Chicago, Houston, and Seattle, as they are the top four metropolitan areas with largest population in U.S., and Seattle, where the first confirmed COVID-19 case was reported [26]. Correlation analysis is performed to check if these two datasets capture similar mobility changes during the epidemic since March 1st, 2020.

As is shown in the Table 3, the produced mobility flow datasets have high correlation coefficients (at least 0.92) with the Descartes Lab’s mobility changes dataset in all five metropolitan areas. It shows that the generated datasets capture similar mobility temporal patterns with other open data sources. As mentioned above, there is no ground-truth in measuring such high resolution dynamic human mobility patterns for the entire population, and as such it is therefore impossible to know which one can characterize human mobility more accurately. However, by cross-referencing other sources, high correlation coefficients indeed show the reliability of our generated mobility flow dataset.

Usage Notes

Different datasets have their own pros and cons. In this data descriptor, we introduce two types of datasets in characterizing human dynamic flows: daily flows and weekly flows, each at three geographic scales (i.e., census tract, county, and state). A detailed description of the statistics and distributions of the datasets may benefit different applications. Here, we discuss the characteristics and limitations of our mobility flow dataset to guide potential usages.

Figure 4 shows the temporal changes of the total number of mobility flows in five metropolitan areas: New York, Los Angeles, Chicago, Houston, and Seattle. Accordingly, the daily flow data provides a more detailed temporal pattern description of human mobility compared to the weekly flow data. As illustrated in Figure 4, the temporally-changing curves have more fluctuations over time as human mobility patterns might be influenced by various factors and individual events (e.g., presidential primary election day or street protests), while weekly flow data reflects more general mobility patterns; the temporal curves for the weekly data are more smooth and stable in comparison to the daily flow data. For example, people may not visit the supermarket everyday and therefore the visitor volumes may vary by day of a week, while the sum of volumes in one week is more stable.

Figure 5 shows the spatial patterns of mobility flow changes during the COVID-19 epidemic based on the weekly flow data. Figure 5A and 5B show the spatial interaction patterns of population flows across the Contiguous U.S. at the state and county scales, respectively. Figure 5C shows the population flow patterns at the census tract scale in the New York metropolitan area, as it has the most confirmed cases. We take three weekly flow data to represent the spatial patterns of mobility flows before (March 2nd to March 8th), during (April 6th to April 12th), and after (May 11th to May 17th) the stay-at-home orders. At all three spatial scales, the movement flows decrease significantly from March to April due to the stay-at-home orders, with certain increases in May with the start of state partial reopenings. The decrease and subsequent increase in human movement flows clearly shows how the outbreak of the epidemic and social distancing-related policies affect human mobility patterns. In particular, according to Figure 5D, during the stay-at-home order period long-range spatial interactions decrease to a small quantity, while most human movement behaviors appear as short-range movements to the adjacent counties. When cities begin to reopen in May, long-term spatial interactions increase at both state scale and county scale.

While we made great efforts to guarantee the reliability of our produced mobility flow datasets and reduce the data uncertainty, a few limitations should be acknowledged.

First, since we acquire mobile phone data from SafeGraph, the privacy policies applied should be considered by the end-user, as they may influence data uncertainty. The weekly flow data is derived from CBG to POI visitor flow metric. Please note that when a CBG has no visitors or has only one visitor who originate from that CBG to one POI, the visit between CBG to POI will not be recorded. If the CBG has 2-4 visitors who originate from that CBG to another POI, the visitor count will be recorded but shown as 1 to enhance differential privacy. Only when the CBG has more than 5 visitors whose home places inside the CBG to one POI will the real visitor count be displayed correctly. Consequently, the least number of visitors from a CBG to POI as well as the weekly flow data computed in one week is 4.

Second, in terms of counting criteria, it should be noted that, for the daily flow data, it records the unique visitors to one CBG in one day, while for the weekly flow data it records the unique visitors to one POI in one week. Due to the different counting methods, the sum of daily flow data in one week (i.e., seven days) are not equal to the weekly flow data. For the daily flow data, which is computed directly based on the daily CBG to CBG visitor flows, it may underestimate the mobility flows to POIs within one CBG. That is, a visitor may visit more than one POI inside that CBG (e.g., different buildings in a campus) during the same day, it would still only be recorded once from the origin CBG to the destination CBG. For the weekly flow
data, which is based on the weekly CBG to POI visitor flows, mobility flows to POIs in one week may be underestimated as a visitor may visit one POI multiple times (e.g., work places) in one week, which would only be counted once as we compute the unique visitor devices rather than raw visits.

In addition, visitor duplication may also exist when aggregating the flows from lower level spatial scales to upper level spatial scales (e.g., from CBG level to census tract scale, county scale, or state scale), and it may lead to the inflation of the inferred dynamic population flows. For example, a user may originate from his/her home CBG and visit two POIs which are located inside different CBGs but the same census tract. Such a visitor should be counted as one unique visitor from the home census tract to the POI census tract. However, when aggregating the visits from CBG to CBG mobility flow to census tract to census tract mobility flow, because the individual travel behaviors cannot be traced, the mobility flows between these two census tract are counted as two and thereby inflate the real mobility flows.

Last but not least, data bias is a common issue for large-scale mobile phone data that may influence the representativeness of our produced dataset. While dynamic mobility flows are inferred from mobile phone applications by users, not everyone in the population has a mobile phone, and not everyone uses smartphone applications, especially elderly people and children. Given these differences in mobile phone usage, age groups and demographic composition might influence the estimated entire population mobility flows.

In conclusion, such a timely-produced dynamic O-D human flow dataset at different geographic scales can help deepen our understanding of human dynamics, inform public health policy making, and support many other social sensing and transportation applications.

Code availability
Data processing and data analysis were performed on a Linux server using the Python version 3.7. All codes used for analysis are available upon request from Y.K. and S.G.

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Author contributions
Research design and conceptualization: S.G., Y.K.; Data collection and processing: Y.K., S.G.; Result analysis: Y.K., S.G., Y.L.; Visualization: M.L., J.R., Y.K., S.G.; Writing: all authors.

Competing interests
The authors declare no competing interests.

Figures

Figure 1: The data processing framework for the mobility flow dataset production.
Figure 2: Spatial distribution of places collected by SafeGraph across the whole United States, created using DataShader package, Python 3.7.

Figure 3: Quantile-Quantile plots of visitor flows and population flows based on weekly flow data in the week of March 2nd to March 8th, 2020. A: at the census tract scale; B: at the county scale; C: at the state scale. The red lines are fitting lines between two distributions.

Figure 4: Temporal patterns of mobility flows in five metropolitan areas: New York, Los Angeles, Chicago, Seattle, and Houston. A: daily visitor flows; B: daily population flows; C: weekly visitor flows; D: weekly population flows. Date range: daily flow data from March 1st to May 24th, 2020, weekly flow data from March 2nd to May 17th, 2020.
Figure 5: Spatial patterns of mobility flows before (March 2nd to March 8th), during (April 6th to April 12th), and after (May 11th to May 17th) the stay-at-home orders at three geographic scales using weekly flow data. A: From state to state across the Contiguous U.S.; B. From county to county across the Contiguous U.S.; C. From census tract to census tract in the New York metropolitan area. Note that the flow dataset includes all 50 states and D.C.; flows in Hawaii and Alaska are not shown in the map.

Tables

Table 1: A sample record of daily CBG to CBG visitors.

| origin census block group | destination census block group | visitors |
|---------------------------|-------------------------------|----------|
| 0123456789xx              | 0123456798xx                 | 10       |
Table 2: A sample record of weekly CBG to POI visitors.

| origin census block group | destination POI ids | visitors |
|---------------------------|--------------------|---------|
| 0123456789xx             | sg:012345xx        | 10      |

Table 3: Pearson’s correlation coefficients between our mobility flow dataset and the ACS commuting flow dataset at county scale.

| Weekly Flow Data          | Date          | Type         | Matched Records | Pearson Correlation Coefficient |
|---------------------------|---------------|--------------|-----------------|---------------------------------|
| Visitor Flows             | 3/2/2020      | Visitor Flows| 102730          | 0.906                           |
| Population Flows          | 3/2/2020      | Population Flows| 102246          | 0.935                           |
| Visitor Flows             | 4/6/2020      | Visitor Flows| 76977           | 0.932                           |
| Visitor Flows             | 4/6/2020      | Visitor Flows| 92297           | 0.935                           |
| Visitor Flows             | 5/11/2020     | Visitor Flows| 94729           | 0.977                           |
| Visitor Flows             | 5/11/2020     | Visitor Flows| 94729           | 0.934                           |

Table 4: Pearson correlation coefficients between the temporal patterns of our daily flow dataset and that of the Descartes Labs dataset.

| Metropolitan Area          | Pearson Correlation Coefficient |
|---------------------------|---------------------------------|
| New York                  | 0.977                           |
| Los Angeles               | 0.956                           |
| Chicago                   | 0.928                           |
| Houston                   | 0.92                            |
| Seattle                   | 0.951                           |

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