The promise of excess mobility analysis: measuring episodic-mobility with geotagged social media data

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Abstract: Human mobility studies have become increasingly important and diverse in the past decade with the support of social media big data that enables human mobility to be measured in a harmonized and rapid manner. However, what is less explored in the current scholarship is episodic mobility as a special type of human mobility defined as the abnormal mobility triggered by episodic events excess to the normal range of mobility at large. Drawing on a large-scale systematic collection of 1.9 billion geotagged Twitter data from 2017 to 2020, this study contributes the first empirical study of episodic mobility by producing a daily Twitter census of visitors at the U.S. county level and proposing multiple statistical approaches to identify and quantify episodic mobility. It is followed by four case studies of episodic mobility in U.S. national wide to showcase the great potential of Twitter data and our proposed method to detect episodic mobility subject to episodic events that occur both regularly and sporadically. This study provides new insights on episodic mobility in terms of its conceptual and methodological framework and empirical knowledge, which enriches the current mobility research paradigm.

Keywords: Twitter, human mobility, episodic events, big data

1. Introduction

Following the movement of population across space has always been a challenge for governments, organizations, and researchers. The study of mobility across different spatial and temporal scales is fraught with difficulties fundamentally based on the paucity of reliable and comparable data, which has caused a bottleneck in researchers' ability to analyze human behaviors and human-environment interactions (Laczko, 2015; Willekens et al., 2016). Tracking human mobility is now more important than ever, along with the evolution of globalization and formation of global transport networks reaching all segments of the society and allowing people to move flexibly with more travel options and lower cost (Weaver and Gahegan, 2007; Haklay, 2013; Coleman et al., 2009). The increasingly interconnected world where distances and time keep shrinking continues to surface new opportunities and challenges (Harvey 1990). Emerging opportunities lie in tourism, travel business, and sharing economy, connecting people and places around the world and advancing mutual economic and cultural bonds; while unprecedented challenges alongside increased human mobility in the past decade were widespread in transnational crimes, undocumented mass migration, or the uncontrollable spread of infectious diseases (e.g., the COVID-19 pandemic). In the face of these challenges, there is an urgent need for new mobility data and measures and analytical methods to be employed in mobility-related studies.

What we have known in the current scholarship is that human mobility was usually measured by static snapshots that provided population estimates or small-scale observations and surveys (Santos et al., 2011; Barbosa et al., 2018; Olabarria et al., 2013). Travel statistics are also regularly used to record the number of people leaving or arriving at a particular location (Compares, 2003; Coburn, 2004). Even though research projects have been able to utilize these data sources, many researchers in the field advocate for a search of innovative data collection methods that permit a unified, comparable, and reliable analysis of current population movements (Bilsborrow, 2002). Recently, we have witnessed many attempts to find new sources of data to dynamically track population movements, both in regular situations (e.g., migration studies) (Kumar et al., 2011; Zagheni and Weber, 2012) and during and after extraordinary events such as mass evacuations caused by impending threats (Martín et al., 2017; Huang et al., 2020a).

During the past years, many researchers interested in investigating phenomena, such as migration, tourism, evacuations, or displacement, have recurred to the use of geospatial digital trace data, also known as passive citizen sensor data. This sensor data, usually generated by digital devices (e.g., mobile phones and tablets) to reflect citizens' daily activities, has been proved to be a rich resource for the study of human mobility. It allows the investigation of large groups of people at multiple spatiotemporal resolutions and has great potentials to produce near real-time results (Martín et al., 2020a; Huang et al., 2021; Wang et al., 2021). Some of the sources of passive citizen sensor data that have been explored are mobile telephone data, smart card data, WI-FI and Bluetooth data, and social media data (Camacho et al., 2021; Wei & Yao, 2021; Stange et al., 2011; Zhao et al., 2021; Zhong et al., 2015; Wu et al. 2014; Liu et al., 2021). However, while these new data sources offer new insights on human behaviors, they are inevitably subject to data limitations, including limited data access as the most common concern, as much of such data is privately owned and not freely disclosed for research purposes. Instead, large-scale social media data that are publicly available, in particular Twitter data, has attracted the attention of many researchers as a possible avenue to study human mobility due to its open-data policy (Hawelka et al., 2014; Huang and Wong, 2015; Jiang et al., 2021; Luo et al., 2016; Jiang et al., 2019).

A recent effort by Martín et al. (2021) examined the possibility of measuring the daily dynamics of population displacement following certain major events using Twitter data. However, what has been less explored in the study by Martín et al. (2021) and other existing mobility studies is episodic mobility as a special type of human mobility defined as the abnormal mobility triggered by episodic events excess to the normal range of mobility from both intra-year and inter-year perspectives. The significance of examining episodic mobility lies in tourism and health planning and policymaking for human adaptation to natural disasters and epidemic crises, particularly in the era of COVID-19.

In order to fulfill the knowledge gaps, this study makes an initial attempt to examine episodic mobility by drawing on a large-scale systematic collection of 1.9 billion geotagged Twitter data from 2017 to 2020, producing a daily Twitter census of visitors at the U.S. county level and proposing multiple statistical approaches to identify and quantify episodic mobility. We design an automatic, statistically robust framework that considers both intra-year and inter-year visitation deviations for detecting abnormal visitation patterns triggered by episodic events at the U.S. county level. Four case studies are presented to showcase the great potential of Twitter data and our proposed method. The conceptual, methodological, and experimental knowledge provided by this study will enrich the current mobility research paradigm and benefit cross-disciplinary studies that demand knowledge of human mobility.

The remaining paper is organized as follows. We first introduce the concept of "excess mobility" and how it is intertwined with modified Z-score and time-series decomposition approaches (Section 2). We then explain the method followed to produce the daily Twitter visitors from geotagged tweets (Section 3). Further, we describe our proposed statistical approaches that incorporate the concept of excess mobility, i.e., modified Z-score coupled with time-series decomposition (Section 4). We further validate the U.S. county-level daily visitor count derived from Twitter against the mobility records collected from 45 million mobile devices that cover 10% of the U.S. population, open-sourced by SafeGraph (https://www.safegraph.com/) (Section 5). Finally, we display some potential applications of the data (Section 6), discuss limitations and future steps (Section 7), and conclude the study (Section 8).

2. Backgrounds

2.1 Episodic mobility and excess mobility analyses

Episodic mobility is a special kind of human mobility defined as the abnormal mobility triggered by episodic events excess to the normal range of mobility at large. Such episodic events can be natural disasters, medical emergencies, tourism events, and/or the spread of infectious diseases. They may trigger sharp changes in human mobility as proactive protective adaptations and reactions to the surrounding environment, including evacuation, resettlement, displacement and/or migration. Studies on episodic mobility enable researchers to detect and quantify abnormal human mobility and to understand the drivers of such mobility.

Temporally sparse official statistics at the aggregated level, such as censuses or registries, have particularly struggled to reflect the temporal sequence of an episodic mobility event. Thus, researchers would often find it very challenging to assess the magnitude, direction and timeframe of episodic mobility (i.e., how many, when and where people moved to and from a place, and whether they returned). These official statistics are often released annually (in best-case scenarios), which makes it very challenging to establish the temporal sequence between the drivers of mobility and the consequences since there may be multiple mobilities occurring in a yearly timeframe, potentially triggered by multiple events and motivations. Thus, it is much needed to analyze episodic mobility at a fine level (e.g., by day or week).

The coarse temporal resolution of official statistics data has made researchers seek alternative methods to study event-triggered mobility (Finch et al., 2010; Fussell et al., 2014). In recent years, geospatial digital trace data seems to be the source of information that has gained more attention and where researchers are placing the emphasis. For instance, call detail records (CDR) were used to track human mobility in Haiti after the 2011 earthquake (Bengtsson et al. 2011). More recently, other researchers have used social media data to determine the magnitude of evacuations and post-disaster displacement after hurricanes (Jiang et al., 2021; Martín et al., 2020b). The great advantage of geospatial digital trace data is the availability of spatiotemporal information that allows us to investigate short events that unfold in days or weeks. However, unlike other small-scale data such as travel surveys, where the researcher can directly ask survey participants about the nature and motivation of their mobility, researchers using large-scale social media data have to assume that human mobility occurring in an emergency or in the aftermath of a disaster were motivated by that event. Weak explanations on the motivations of mobility have been one of the main critiques in mobility studies based on geospatial digital trace data — what this study aims to fulfill.

2.2 Social media, modified Z score, and time series decomposition: a potential solution

The concept of “excess mobility” is borrowed from “excess mortality”, a commonly used term in epidemiology and disaster studies, which provides the estimation of the additional number of mortality within a given time period in a geographical region (e.g., country), compared to the estimate of mortality had the events not occurred (Santos-Burgoa et al. 2018; Fouillet et al., 2006). Essentially, excess analysis demands the establishment of references, i.e., previous mortality records for counterfactual estimation (Brodersen et al., 2015). When applying this concept to mobility, we argue that excess episodic-mobility analysis refers to the analytical framework that derives mobility deviations by comparing mobility records at normal situations in an intra-year or inter-year manner. In intra-year analyses, episodic events drive mobility records in a certain region to deviate from their normal situations, usually reflected by sudden increases or decreases of mobility within that year. Inter-year analyses often compare mobility records in a given year to the mobility records reference year(s), often estimated using the same time period in the preceding year or averaged over several preceding years.

As mobility data has increasingly grown in volume over the past decade, thanks to ubiquitous localization technologies for capturing human mobility flows, mobility records have been accumulated over the years, establishing a great venue where intra-year and inter-year comparison of records can happen. The rising of social media platforms since the early 2010s has received much attention and offers a novel solution to document human mobility at fine temporal granularity in an easily accessible manner, thanks to the timely geographical information from global/national social sensing networks constituted by millions of social media users (Huang et al., 2020a; Liu et al., 2021; Li et al., 2021a). After years of data accumulation, mobility records derived from social media platforms now feature a relatively long temporal coverage that enables year-on-year comparison, greatly facilitating excess mobility analyses.

In this study, we document a large-scale collection of daily Twitter visitors at the county level in the United States. For intra-year comparison, to measure how visitor counts on a certain day deviate from yearly visitor count distribution, traditional Z score statistics that describe a value's relationship to the mean can be implemented (e.g., Martín et al., 2021). However, considering the skewness of visitor distribution (see Figure A in the Appendix) and the existence of outliers (extreme values) evidenced by many existing studies (Martín et al., 2021; Jurdak et al., 2015), a more robust approach, i.e., modified Z score statistics, is preferred and has been adopted by many event detection studies (Huang et al., 2019; Seem, 2007). As for inter-year comparison, one of the most commonly adopted techniques to derive references against which records from other years can compare is time series decomposition, which has been widely implemented in various domains that include remote sensing (Lambert et al., 2013; Kong et al., 2015), travel analysis (Xu et al., 2016; Huo et al., 2019), economy (Zarnowitz and Ozyildirim, 2006; Beveridge and Nelson, 1981), to list a few. From the perspective of human mobility, visitor counts can exhibit a variety of yearly patterns; therefore, the extraction of the underlying trend components establishes valuable baselines that assist in the detection of systematic or unsystematic deviations caused by episodic events. For instance, Zhu and Guo (2017) decomposed the time series of taxi trips in Manhattan, New York City, into various components for urban event detection. Omkar and Kumar (2017) decomposed traffic volume data to investigate the hidden travel patterns with the ultimate goal of performing flow forecasting. More recent efforts have incorporated human mobility time-series decomposition in tackling COVID-19 issues (da Silva et al., 2021; Singhal et al., 2020).

Thus, we argue that coupling the accumulated mobility records (number of visitors in this study) from social media platforms with techniques that involve modified Z score and time-series decomposition approach establishes a great venue where the impacts of episodic events on geospatial digital trace data can be thoroughly investigated in a rapid manner.

3. Datasets

3.1 Twitter data collection and preprocessing

We collected over 1.9 billion geotagged Twitter posts (hereinafter termed as tweets) that cover the conterminous U.S. using the Twitter Streaming Application Programming Interface (API). These tweets were posted from January 1, 2017 to December 31, 2020 (four-year coverage). We stored these tweets in a computing cluster and processed them with Apache Hive, Impala, and GIS Tools for Hadoop by Esri (Li et al., 2021). The locational accuracy of a tweet largely varies and depends on the specific users' setting (Huang et al., 2020a). As our interest is to investigate the count of visitors at the county level, we only include geotagged tweets (tweets with locational information) that can be located and aggregated into a certain spatial scale, equal or finer than a county (e.g., exact coordinates, point of interests, cities, etc.). We further derived Twitter users' home locations and used such information to calculate the daily number of visitors at the U.S. county level. We filtered out the non-human tweets, such as automated weather reports, job offers, and advertising, by exploring the tweet source from which application tweets are posted. For example, tweets automatically posted for job offers from the source TweetMyJOBS and CareerArc were removed. Other details regarding the preprocessing procedure and workflow of retrieving daily visitor count can be found in Martín et al. (2021). In addition, we excluded eight days (May 22 to May 29, 2019) from the analytical timeframe due to the missing data in this time period.

3.2 Reference dataset (SafeGraph Social Distancing Metrics)

To validate to what extent that our county-level Twitter data of daily visitors would be able to represent the mobility of the general population, we compared the daily visitor count calculated by Twitter data to that calculated from the Social Distancing Metrics, open-sourced by SafeGraph (https://www.safegraph.com/), a company that provides aggregated location information from anonymized digital devices via numerous applications. SafeGragh's data are collected using a panel of Global Positioning System points from around 45 million anonymous mobile devices, covering around 10% of the U.S. population (Huang et al. 2020b; SafeGraph, 2020). Such a high penetration ratio of SafeGraph data makes it an ideal source to validate the representativeness of Twitter data. SafeGraph first determined the home locations of devices using their common nighttime locations over a six-week period and further reported their daily movement pattern at the Census Block Group (CBG) level. To protect users' privacy, SafeGraph excludes CBG information if fewer than five devices visited an establishment in a month from a given CBG.

For comparability, we derived visitor count using SafeGragh's movement patterns and upscaled the statistics from the CBG level to the county level, making them consistent in spatial scales with our Twitter data. It is worth noting that SafeGragh's Social Distancing Metrics has a limited temporal coverage from January 1, 2019, to April 16, 2021 and it is no longer available after April 16, 2021.

4. Methods

4.1 Modified Z score (intra-year comparison)

For a certain county in a given year, its daily visitor count is represented by $V = \{v_1, v_2, \ldots, v_n\}$ ($n = 365$ in ordinary years and $n = 366$ in leap years). Given the distribution pattern of V, we aim to measure the degree of how the visitor count on a certain day deviates from its yearly visitor count distribution. We applied the modified Z score, an improved and more robust standardization approach compared to the traditional Z score, thanks to its capability in anomaly tolerance. The calculation of modified Z score for a given day i (z_i^{mod}) is calculated following:

$$z_i^{mod} = \frac{\alpha_1(v_i - \tilde{v})}{MAD} \tag{1}$$

where Z_i^{mod} denotes the modified Z score of the visitor count on day i, α_1 is a constant of 0.6745 (Huang et al., 2019; Iglewicz and Hoaglin, 1993), v_i denotes the visitor count of a certain county on day i. $\tilde{v}$ denotes the median value of V. MAD, suggesting median absolute deviation, is further calculated by taking the median of the absolute deviations from the median:

$$MAD = median\{|v_i - \tilde{v}|\} \tag{2}$$

When $MAD = 0$, z_i^{mod} is modified as:

$$z_i^{mod} = \frac{\alpha_2(v_i - \tilde{v})}{MeanAD} \tag{3}$$

where α_2 is a constant of 0.7966 (Iglewicz and Hoaglin, 1993) and $MeanAD$, suggesting mean absolute deviation, is calculated by taking the mean of the absolute deviations from the median:

$$MeanAD = mean\{|v_i - \tilde{v}|\} \tag{4}$$

4.2 Time series decomposition (inter-year comparison)

After the construction of the time series of $Z^{mod} = \{z_1^{mod}, z_1^{mod}, \ldots, z_n^{mod}\}$ from $V = \{v_1, v_2, \ldots, v_n\}$, we further decompose Z^{mod} using seasonal-trend decomposition with locally estimated scatterplot smoothing (STL) (Cleveland et al., 1990), a versatile and robust time series decomposing method the considers non-linear relationships with a high tolerance to outliers. The STL algorithm decomposes the time series Z into a trend component (T) that suggests the long-term progression of a time series, including the upward, downward, or periodic tendency, a seasonal component (S) that summaries seasonality with repetitive patterns over time, and an irregular component (e) (i.e., noises) that describes random, irregular influences, suggesting the remainder of the time series after other trend and seasonal components have been removed. In a selected reference year (or the average from multiple reference years), the modified Z score on day i, i.e., Z_i^{mod}, can be decomposed following (Cleveland et al., 1990):

$$Z_i^{mod} = T_i + S_i + e_i \tag{5}$$

where T_i, S_i, and e_i denote the trend, seasonal, and irregular components, respectively, on day i.

The STL decomposition procedure follows the three major steps:

Step 1: Initializing trend component $T_i^{(0)}$ and irregular component $e_i^{(0)}$.

Step 2 (Outer Loop): Calculating robustness weights. Run $n_{(0)}$ times:

- Calculating e_i
- Calculating robustness weight $p_i = \left(1 - \left(\frac{|e_i|}{h}\right)^2\right)^2$ if $0 \le \frac{|e_i|}{h} \le 1$. For other $\frac{|e_i|}{h}$, $p_i = 0$. Note that $h = 6 * median(|e_i|)$ and $p_i = 1$ in the initial loop.

Step 3 (Inner Loop): calculating trend and seasonal components in an iterative manner. Run $n_{(i)}$ times:

- *Detrending:* $Z_i^{mod} - T_i^{(m)}$, where m denotes the loop number.
- *Smoothing subseries:* given the user-defined periodicity k ($k = 12$ in this study, reflecting the 12 months in a year), the detrended time series is divided into k subseries, with each subseries loess smoothed, producing a temporary seasonal time series C^{m+1}.

- *Low-pass filtering:* A low pass filter is applied to C^{m+1} to derive L^{m+1}.
- *Detrending of subseries:* $S^{m+1} = C^{m+1} - L^{m+1}$, where S^{m+1} suggests the $(m+1)^{th}$ estimation of the seasonal component.
- *Deseasonalizing:* $Z^{mod} - S^{m+1}$
- *Trend smoothing:* the deseasonalized time series, i.e., $Z^{mod} - S^{m+1}$, is further loess smoothed, yielding the $(m+1)^{th}$ estimation of the trend component, i.e., T^{m+1}.

After these three steps, the trend component, i.e., $T = \{T_1, T_2, \dots, T_n\}$ is derived. Here, we denote the trend component from the reference year(s) and the trend component from the target year as T^{ref} and T^{tar}, respectively. Note that a short period of data missing occurred from May 22 to May 29 in 2019. When deriving the T^{ref}, these missing days were discarded, if T^{2019} was involved in the T^{ref} calculation. We further calculate the difference between these two trend components, i.e., $T^{diff} = T^{tar} - T^{ref}$, and define anomalies caused by episodic events as: $|T^{diff}| > \alpha$, where α is a user-defined threshold. Days that satisfy the condition of $T^{diff} > \alpha$ experience a significant increase in visitors in the target year compared to the reference year(s). On the contrary, days that satisfy the condition of $T^{diff} < -\alpha$ experience a significant decrease in visitors in the target year compared to the reference year(s). The choice of α is empirical, as a larger α denotes a stricter detection criterion while a smaller α denotes otherwise. In this study, we set $\alpha = 1$.

5. Validation against SafeGraph

Given the high penetration rate of SafeGraph data (though not a perfect representation of the entire population), we regard the visitor counts by SafeGraph as a ground truth.

SafeGraph serves as a great reference to validate our Twitter-derived visitor counts. The temporal coverage of Twitter and SafeGraph data overlaps in the years 2019 and 2020. We selected the year 2019 as the baseline for the comparison study, as the mobility patterns in 2020 were greatly affected by the COVID-19 pandemic. Due to the sparseness of geotagged Twitter data, we further selected counties with a median daily visitor count larger than 30, leading to a total of 324 counties included in the validation. These counties are generally heavily populated (or located nearby densely populated counties) with sufficient Twitter-derived visitor records that would ensure the statistical robustness and scientific soundness of the validation process.

Figure 1 shows the comparison between the monthly median of visitors derived from Twitter and SafeGraph at different months in the year 2019. In the monthly scatterplots (Figure 1), we note that there is a strong positive linear relationship between visitors documented by Twitter and SafeGraph, evidenced by the high Pearson correlation coefficient (Pearson's r) values in all months. The highest correlation coefficient occurred in January ($r = 0.896$) and the lowest in April ($r = 0.846$). In general, we observe that the correlation of visitors from Twitter and SafeGraph maintains at a high and stable level across the entire year of 2019. Figure 2 is an integrated plot by showing median monthly visitor counts from these two sources from all months in 2019. The annual statistics in Figure 2, again, proves the strong correlation between Twitter and SafeGraph data ($r = 0.860$).

While we are aware that SafeGraph data do not fully represent the human mobility patterns of the general population, its high penetration ratio and observed strong positive correlation with Twitter data confirm the feasibility of using Twitter data as a proxy to mobility patterns from heavily sampled records. In addition, the limited availability of SafeGraph data (Social Distancing Metrics is only freely available during the COVID-19 pandemic till April 16, 2021) demonstrates the necessity of seeking geotagged social media as the alternative data source to supplement the scarcity of current mobility datasets.

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6. Case Studies

6.1 Case 1: Yellowstone National Park and Grand Teton National Park (Teton County, Wyoming)

Teton County is located northwest of Wyoming (Figure 3a). It contains two most popular national parks in the United States: the Yellowstone National Park (2020 U.S. national park rank: 2; 3.8 million visitors) and part of the Grand Teton National Park (2020 U.S. national park rank: 5; 3.3 million visitors) (National Park Service, 2021a). Though Teton county has a small number of permanent residents, it welcomed 1,837,000 overnight visitors in 2018 (Jackson Hole Travel & Tourism Board, 2020). Tourism is also one of Teton County's biggest industries that travelers support 27% of the county's total private-industry employment (Jackson Hole Travel & Tourism Board, 2020). These two parks are popular destinations for tourists year-round, especially from June to September (National Park Service, 2021b). The visitation derived from Twitter confirms the above statement, as the trends of modified Z scores increased dramatically from June to September in all the selected years from 2017 to 2020 (Figure 3b).

As the solar eclipse passed over the U.S. on August 21, 2017, both parks were popular observation points (Figure 3a), which set tourism records in both parks in August 2017. The total solar eclipse can be viewed in the Grand Teton National Park. Therefore, there was about a 40% increase in park visits surrounding August 21, 2017, compared to the previous visitation record at the same time in 2015 and 2016 (Moen, 2017). The most significant increase appeared during the days around the solar eclipse. This historical moment was well captured by our Twitter visitation, as the trend component of modified Z scores almost reached 3 in mid-August 2017 (Figure 3b). We compare trend components of modified Z scores by setting the year 2017 as the target year (T^{tar}) and years 2018, 2019, and 2020 as the reference years (T^{ref}) (Figure 3c). The red color marked in the x-axis indicates that the target year had notably higher modified Z scores compared with the reference years ($T^{diff} > \alpha$), which suggests that a significant increase in visitation occurred in mid-August 2017, compared with the following years (Figure 3c).

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6.2 Case 2: Myrtle Beach (Horry County, South Carolina)

Horry County is the easternmost county of South Carolina, with Myrtle Beach its largest city with 60 miles of the coastline of the Atlantic Ocean (Figure 4a). Myrtle Beach is also one of the most popular East Coast family vacation destinations in the U.S. Summertime, from June to August, is the most popular time to visit Myrtle Beach. Though the monthly tourist data is not available to the public, this trend was captured by the trend components of modified Z scores generated using Twitter's data. We identified a significantly increased modified Z score between June and August in the city in all the selected years (Figure 4b). These numbers peaked in July, suggesting the highest tourism volume appeared in July (Figure 4b). The COVID-19 pandemic heavily impacted the city's tourism industry, as the city experienced a significant drop in hotel reservations in July and August in 2020 compared to the same period in 2019 (Karacostas, 2020). We then visualize the impact of the COVID-19 pandemic by comparing the trend component of modified Z scores in 2020 (T^{tar}) with the one in 2017, 2018, and 2019 (T^{ref}) (Figure

4c). The blue color marked in the x-axis indicates that the target year had lower modified Z scores compared with the reference years ($T^{diff} > \alpha$), suggesting a notable decrease in tourism volume between June and August in 2020 compared with the previous years, due to the impact of the COVID-19 pandemic (Figure 4c). The above results indicate that Twitter-derived visitation patterns revealed by our proposed excess mobility analytics can accurately reflect tourism volumes in a timely manner. Stakeholders and researchers are suggested to use this resource to understand tourists' preferences and to improve business planning and performance.

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6.3 Case 3: Southern 500 NASCAR race (Darlington County, South Carolina)

The Southern 500 is a National Association for Stock Car Auto Racing (NASCAR) Cup Series stock car race in Darlington, South Carolina, US (Figure 5a). From 1950 to 2003, and again since 2015, this race has been held on Labor Day weekend (around the first week of September). Darlington is a local county that normally has a low visitation during the year (Figure 5b); however, a sharp increase of visitors is depicted during the first week of September in 2017-2019 (modified Z score around 10.3, 14.0 and 16.0 in 2017, 2018, and 2019 respectively) that are highly likely to associate with the Southern 500. In 2020, the magnitude of such an increase of visitors had been reduced largely (modified Z score around 2.5 in 2020) compared to 2017-2019, as detected by the dark blue in the bottom bar of Figure 5c, indicating a sharp reduction of visitors in 2020 possibly due to the COVID-19 restrictions. It is also noteworthy that another increase of visitors is observed in the mid of May 2020, with the possible reason awaiting further exploration. The detection of such sport or recreational events by Twitter data can be implemented in other counties where similar epidotic events occurred. For example, in our experiments, Summit County in Utah has observed an increase in visitors in the last week of January in tandem with the commencement of the Sundance Film Festival in Park City as one of the largest independent film festivals in the US. Orlean County in Louisiana is detected with a sharp increase of visitors in the last week of February as the Mardi Gras carnival took place in New Orleans each year. Pershing County in Nevada is another typical example that a sharp increase of visitors is detected by Twitter data during the end of August and the first week of September when the Burning Man Festival as an iconic counterculture event takes place in the Black Rock Desert of northern Nevada each year. During this festival, a temporary city in the desert is built as a utopia, drawing visitors from around the globe.

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6.4 Case 4: Spatial distribution of modified Z score on Christmas Day

Here, we further examine the spatial distribution of modified Z scores at the national level on Christmas day (December 25) (Figure 6). A blue theme (light to dark blue) indicates a decrease of visitors (modified Z score smaller than -0.5), while a red theme (light to dark red) indicates an increase of visitors (modified Z score larger than 0.5). On Christmas Day, in the years of 2017-2019, counties with increased visitors (red with modified Z score larger than 1.5) are observed to spread out in the whole US mainland, while a number of large counties in Arizona, Utah, Nevada, Nebraska, Colorado, and New Mexico experience a reduction of visitors (Figure 6a-c). However, the number of counties with increased visitors in 2020 is much less than that in 2017-2019, while the number of counties with decreased visitors in 2020 is much more than that in 2017-2019 (Figure 6d), which can be possibly explained by the dampened travel willingness due to the COVID-19 pandemic. The above results indicate that visitation patterns captured by Twitter data using the proposed method in this study have the capability to reflect the episodic events that occur regularly in each year or happen sporadically on a particular date.

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7. Limitations and future steps

It is necessary to acknowledge several limitations of this work and provide guidelines for future studies. First, while the correlation between visitors derived from Twitter and SafeGraph (a highly sampled human mobility dataset) reveals a Pearson's r of 0.860 in 2019, whether human mobility patterns derived from Twitter can be generalized to the entire population deserves further investigation. The representativeness issue of Twitter has been noted by many studies, as it may not ideally reflect the characteristics of the general population as a whole and is undersampled towards the elderly, the poor, and those who do not have access to digital devices and are not willing to share information online (Jiang et al., 2019; Martín et al., 2017; Hu et al., 2021). Acknowledging this representativeness shortcoming from Twitter data, we believe the human mobility dynamics with a fine spatiotemporal granularity from Twitter contributes to a wide range of studies that require rapid and large-scale human mobility monitoring. Future studies can explore the possibility of fusing Twitter data with other mobility sources, aiming to derive improved visitor counts captured from a wider population spectrum.

Second, despite its "Big Data" nature, the available geotagged tweets that can be used for visitor counts are still insufficient to derive stable time series of visitors in sparsely populated counties at a temporal resolution of daily, posing further challenges to the time-series decomposition approach and leading to indecipherable patterns from their trend components. Such data sparsity results from the active data collection mechanism from Twitter (i.e., users need to post information before his/her locations can be captured), which unavoidably leads to a diluted amount of trajectory data from both spatial and temporal perspectives (Huang et al. 2020a). In addition, depending on users' specific settings, the locational accuracy of geotagged tweets varies. For instance, the Twitter data used in this study consists of about 80% of tweets that can be located to the place level (city, neighborhood, and point of interest), while the remaining tweets are with coordinates (latitude and longitude) (Li et al. 2021b; Martín et al., 2021). In light of the small proportion of tweets that can be geotagged, further efforts can incorporate geoparsing, a process of converting text descriptions of places to unambiguous geographic identifiers (Cheng et al., 2010), to better derive Twitter users' location. In certain cases, users' profiles can also provide locational information with sufficient accuracy that supports the localization of users' home locations.

Third, we involve the modified Z score coupled with time-series decomposition techniques to investigate visitation patterns driven by episodic events. Although modified Z score with strong robustness is an improved version of the traditional Z score, its limitation should not be ignored. For rural counties with no documentation of visitors most time of the year, the MAD (see Equation 1), i.e., the median of the absolute deviations from the median, tends to be 0. Consequently, the calculation of modified Z score for these counties is transitioned to the utilization of $MeanAD$ (see Equations 3 and 4), i.e., the mean of the absolute deviations from the median. Such a calculation transition introduces uncertainties when cross-comparing modified Z scores from different counties. In addition, a county's yearly modified Z scores time series is subject to its yearly distribution of visitor counts. Thus, a multi-year comparison of derived trend components of the modified Z score is valid when a county's yearly distributions of visitor counts (in terms of median and mean values) do not differ in a significant manner. Further efforts can be made towards the investigation of other supervised/unsupervised time-series handling approaches for better identification of mobility anomalies caused by episodic events.

In terms of future developments, we plan to apply the proposed methods to regions beyond the U.S. and further extend our designed cyberinfrastructure to a global scale, taking better advantage of the global coverage of Twitter data. We also plan to open-source our Twitter-based mobility dataset and develop an interactive online tool that allows the visualization of visitors at various geographic levels with downloadable and ready-to-use multi-scale visitor counts to support wider community needs. We believe rapid, large-scale monitoring of visitors from social media has the potential to benefit a variety of fields that demand knowledge of human movement with fine spatiotemporal granularity, including disease monitoring and modeling, transportation planning, disaster management, tourism, and migration. Given the capability of geotagged Twitter data in generating Origin-Destination matrices, we plan to further explore the spatiotemporal dynamics of users' origins, hoping to better understand the mechanism behind the detected episodic events. In addition, we plan to involve the contextual knowledge that can be derived from Twitter posts via text mining and image processing techniques, aiming to provide better situational awareness that facilitates our understanding of the reasons behind observed visitation anomalies due to episodic events.

8. Conclusion

Monitoring human mobility across space triggered by episodic events has always been a challenge for governments, organizations, and researchers. The growing popularity of social media provides a great venue where human mobility can be measured in a harmonized, less privacy-concerning, and rapid manner by taking advantage of the digital trace data from this unique crowdsourcing platform.

This study contributes an empirical study of a special type of human mobility which has been rarely explored in the current scholarship — episodic mobility, defined as the abnormal mobility triggered by episodic events excess to the normal range of mobility at large. Drawing on a large-scale systematic collection of Twitter data from 2017 to 2020, we produce a daily Twitter census of visitors at the U.S. county level and propose multiple statistical approaches, including modified Z score statistics and a time-series decomposition technique, to identify and quantify episodic mobility. It is followed by four case studies of episodic mobility in U.S. national wide to showcase the great potential of Twitter data and our proposed method to detect episodic mobility.

For intra-year comparison, modified Z score statistics are used to measure how visitor counts on a certain day deviate from yearly visitor count distribution. As for inter-year comparison, a versatile and robust time series decomposing method, i.e., seasonal-trend decomposition with locally estimated scatterplot smoothing (STL), is applied to derive the yearly trend components, thus setting up baselines that facilitate the detection of systematic or unsystematic cross-year deviations. By validating Twitter-derived visitor counts against the SafeGraph mobility records collected from 45 million mobile devices, we illustrate the feasibility of using Twitter mobility patterns as a proxy to mobility patterns from heavily sampled mobile records, evidenced by their strong positive correlation with a Pearson's r reaching 0.860. We further described our developed interactive visualization portal that currently allows interactive exploration of the U.S. county-level Twitter-derived daily visitor counts in years 2017, 2018, 2019, and 2020. We further present four case studies to demonstrate how mobility patterns driven by episodic events can be measured, including 1) Teton County, Wyoming (Yellowstone National Park and Grand Teton National Park); 2) Horry County, South Carolina (Myrtle Beach); 3) Darlington County, South Carolina (the Southern 500 NASCAR race); and 4) Christmas days from 2017 to 2020. These demonstrations indicate that visitation patterns captured by Twitter data using the proposed method have the capability to reflect the episodic events that occur regularly or sporadically.

For future developments, we intend to take better advantage of the global coverage of Twitter data by applying the proposed methods and extending our designed cyberinfrastructure to a global scale. We also plan to open-source our Twitter-derived visitation dataset with an interactive online tool that allows multi-scale visualization downloadable options to support wider community needs. We believe conceptual, methodological, and experimental knowledge provided by this study is expected to benefit a wide range of studies that demand knowledge of human movement with fine spatiotemporal granularity.

Data availability statement

The computed daily modified Z scores and the derived trend components at the US county level for the four years (from 2017 to 2020) are provided as manuscript supplementary material. The Twitter data was collected using Twitter's public Streaming API from the public domain following Twitter's Developer Agreement. Following Twitter's policy on "Redistribution of Twitter content" (https://developer.twitter.com/en/developer-terms/moreon-restricted-use-cases), the geotagged tweet IDs used in this analysis will be provided upon request. The Social Distancing Metrics was live during the peak of the COVID-19 pandemic and is no longer supported (https://docs.safegraph.com/docs/social-distancing-metrics).

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Appendix

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List of Figures

Figure 6. The spatial distribution of modified Z score of Twitter visitors on December 25 in years a) 2017, b) 2018, c) 2019, and d) 2020. **[two-column]**

Figure A. The histogram of county-level total visits from Twitter in 2019. **[one-column]**