

Using Georeferenced Twitter Data to Estimate Pedestrian Traffic in an Urban Road Network

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Abstract

Since existing methods to estimate the pedestrian activity in an urban area are data-intensive, we ask the question whether just georeferenced Twitter data can be a viable proxy for inferring pedestrian activity. Walking is often the mode of the last leg reaching an activity location, from where, presumably, the tweets originate. This study analyses this question in three steps. First, we use correlation analysis to assess whether georeferenced Twitter data can be used as a viable proxy for inferring pedestrian activity. Then we adopt standard regression analysis to estimate pedestrian traffic at existing pedestrian sensor locations using georeferenced tweets alone. Thirdly, exploiting the results above, we estimate the hourly pedestrian traffic counts at every segment of the study area network for every hour of every day of the week. Results show a fair correlation between tweets and pedestrian counts, in contrast to counts of other modes of travelling. Thus, this method contributes a non-data-intensive approach for estimating pedestrian activity. Since Twitter is an omnipresent, publicly available data source, this study transcends the boundaries of geographic transferability and scalability, unlike its more traditional counterparts.

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1 Introduction

1.1 Background and motivation

Urban traffic monitoring and analysis is increasingly important with the ever-growing urban population. Urban traffic consists of two major modes of travel, namely the vehicular mode (automobile, bicycle, transit) and the pedestrian mode [38]. Research on urban vehicular traffic has been popular for the past five or six decades owing to increased number of motorised vehicles on the road and the consequent challenges related to traffic congestion, competition for space and consumption of resources. On the contrary, the focus on pedestrians is more recent with the authorities now spending more resources on developing infrastructure for active mobility (non-motorised forms of transport such as biking and walking) to curb the detrimental impact of the motorised modes on public health and climate.

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While walking is the most common and essential travel mode as almost all places are accessible on foot [39, 13], several studies have shown the benefits of walking with respect to a person's physical and mental health [3, 18, 14]. On a larger scale, walking generates indirect public health benefits by reducing the use of automobiles, consequently reducing traffic congestion, energy consumption, air and noise pollution, the overall level of traffic danger, and thus offering more liveable communities [26, 37]. Besides public health, pedestrian activity is an important factor in urban planning, transportation management and decisions affecting land use and real estate. Analytical insights on pedestrian activity assists governing authorities to estimate demand with greater accuracy and allocate resources accordingly, which, in turn, improves operations.

Owing to the late rise in popularity of research relating to the pedestrian mode (being overlooked for decades), datasets representing pedestrian activity and movement are limited as compared to its motorised counterparts, more so in developing nations. As a result, most studies are still based on the traditional data collection methods of questionnaire surveys, manual counting, and tracking people's movements using GPS devices and smartphones [25, 2, 31, 9, 30, 5, 27]. While these methods are effective, they involve significant monetary costs and suffer from the issues of scalability and transferability in both space and time. Moreover, some of these forms of data collection such as GPS tracking, are highly privacy-sensitive [17]. On the other hand, traditional pedestrian volume estimation studies [22, 31, 9] are dependent on multiple, highly localised, predictor datasets which are not available in most places. Hence, there is a growing necessity for cheap, publicly available, omnipresent proxy data which transcends the boundaries of scalability and transferability. In this regard, location-based social media data, especially Twitter, has gained increasing attention by researchers who have used it to tackle a host of real-world problems including the detection and prediction of vehicular traffic levels [32], unusual levels of vehicular traffic congestion, accidents and disruptions [10, 8, 35], pedestrian congestion [34] and crowd movements at various spatio-temporal scales [7, 4].

1.2 Related work

There is limited systematic research comparing the nature of association of location-based social media data with varying urban travel modes to investigate the possibility that some modes are better represented by such data as compared to the others. While [32] have shown that Twitter and Instagram data can be used as a predictor for actual vehicular traffic by using Odds Ratio, Risk Ratio and RT-DBSCAN, the nature of association was drawn from comparing only the abnormalities of social media distribution and vehicular traffic volume. Since their work intends to identify traffic congestion in near-real time, their methods are limited to successfully differentiating between normal and anomalous traffic volumes. Although [7] and [4] have predicted crowd flow using Twitter, their study is also limited to outlier detection and anomalous behaviour resulting from events. On the other hand, [34] predicted pedestrian congestion using georeferenced tweet counts but did neither report any validation, nor any evidence of association between tweets and pedestrian congestion in the first place. In contrast to the aforementioned literature, this study investigates the possibility of using georeferenced tweets as a viable proxy for predicting pedestrian traffic and shows how tweet counts can be used for prediction of pedestrian traffic at high spatio-temporal resolution.

Other studies have used more traditional approaches of estimating pedestrian traffic at locations by quantifying the influence of multiple predictor variables. [22] presented a model to estimate the pedestrian volumes for street intersections. The study found that population

and job density, local transit access, and land use mix had the strongest explanatory power on variances of pedestrian volume. [31] used a log-linear regression model to identify statistically significant relationships between annual pedestrian volume at road intersections and predictor variables such as land use, transportation system, local environment and socio-economic characteristics surrounding the intersections. Similarly, [9] proposed a scalable approach by using regression models to predict pedestrian volume at road intersections using multiple infrastructural datasets and extrapolate at locations where count data was absent. All these studies are highly data-intensive and are dependent on the spatio-temporal granularity of the datasets representing the explanatory variables.

Among other techniques, the space syntax tool stands out for being less data-intensive and relying only on street network data [11]. While this configurational approach has been used to predict pedestrian movement to an acceptable extent (roughly 60%) [21] in urban spaces, it is well-studied and has a well-developed methodology. But, existing literature has not employed social media data, or even investigated, in the first place, whether it can be used as a measure of estimating the number of pedestrians at a given location at a given time period. On the contrary, this study proposes a novel approach which is not only a scalable, but also transferable and non-data intensive by only using publicly available georeferenced Twitter data with fine granularity instead of employing multiple datasets.

1.3 Research hypothesis and objectives

This study aims to prove the hypothesis that georeferenced Twitter traffic can be used as a viable proxy for estimating pedestrian counts under specific conditions of space and time, with a certain degree of accuracy. The objectives of this paper are:

1. To show the existence of a strong positive correlation between georeferenced Twitter traffic and pedestrian traffic and that this correlation is stronger than vehicular traffic,
2. To develop a scalable and transferable method that predicts pedestrian traffic with reasonable accuracy, at any location in an urban network using only georeferenced tweet counts with high spatial and temporal granularity.

To attain the stated objectives, this study makes use of publicly available georeferenced Twitter data, pedestrian count data made available by the City of Melbourne, and vehicular traffic data from SCATS made available by the Victorian Government.

Overall, the contributions of this study are three-fold.

1. In the first step, this study implements correlation analysis to understand the association between georeferenced Twitter traffic and two major urban travel modes, pedestrian and vehicular traffic, by looking at the nature of correlations and the spatio-temporal patterns of variation of correlation. It compares the results across the two travel modes to understand whether one mode is more strongly associated with georeferenced tweets under certain conditions of space-time and hence tweets can be inferred as a viable proxy for that mode.
2. Based on the findings from the first step, which reveals the existence of a relatively stronger and more statistically significant correlation between Twitter traffic and pedestrian traffic as compared to vehicular traffic, the second step of this study uses standard regression analysis to estimate pedestrian traffic and the resultant estimation errors at existing pedestrian sensor locations, at any given hour of any day of the week. The method is geographically transferable and is able to estimate pedestrian traffic at the finest level of spatial granularity.
3. In the final step, this study predicts pedestrian traffic at every segment of the study area network (even where pedestrian counts are not available) at hourly intervals of any given date using georeferenced tweet counts.

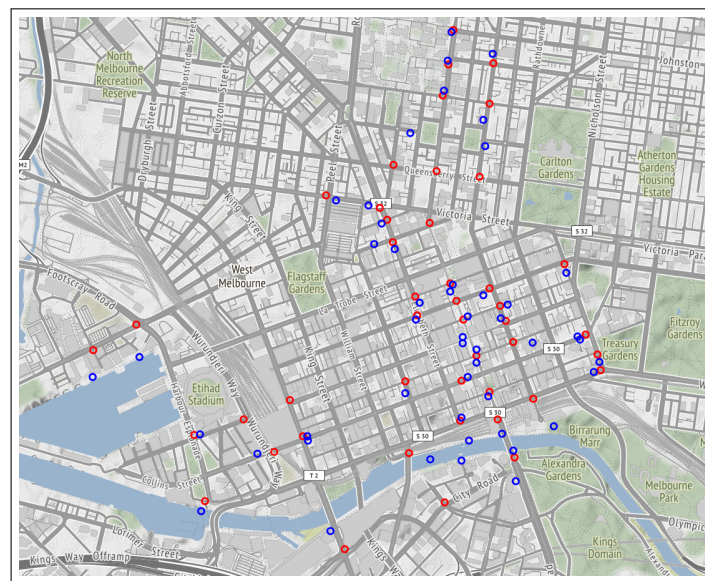
2 Data overview

2.1 Pedestrian counts dataset

The City of Melbourne had developed an automated pedestrian counting system in 2009 to better understand pedestrian activity within the municipality. Using non-vision based sensors installed at multiple strategic locations in its administrative area (covering the Central Business District and its neighbouring suburbs), it collects counts of pedestrians on an hourly basis. The open dataset contains hourly pedestrian counts since 2009 and is updated on a monthly basis. The dataset is structured with the following information:

1. Sensor ID
2. Sensor location (street name)
3. Coordinates of sensor location (latitude, longitude)
4. Hourly pedestrian count
5. Detailed timestamp (date, day of the week, hour of the day)

During the period of data collection for this study (January to April 2018) there were 49 active sensor locations in the city. Figure 1 shows the locations of the pedestrian sensors (blue markers).



■ **Figure 1** Locations of pedestrian sensors (blue) and SCATS sensors (red) in the City of Melbourne.

2.2 Vehicular counts dataset

The official source of the vehicle count data for the cities in Australia is based on the Sydney Coordinated Adaptive Traffic System (SCATS, www.scats.com.au). Recordings are made at intervals of 15 minutes and are available for download from the VicRoads website (www.vicroads.gov.au). Hourly vehicular traffic for each of the 45 sensor locations in terms of counts of vehicles were collected for the period of March 2018. Figure 1 shows the locations of the pedestrian sensors (red markers).

2.3 Twitter dataset

The Australian Urban Research Infrastructure Network (AURIN, www.aurin.org.au) has harvested tweets originating from all major cities of Australia from July 2014 to May 2018 using Twitter's Public Streaming API which allows for a real-time collection of a random sample of tweets. The collection of tweets was not continuous as the dataset contains significant time gaps (April to July 2015, March 2016, May 2016 to May 2017). Similar to previous studies conducted in the domain of spatial information using Twitter data, this research will rely only on precisely georeferenced tweets (tweets with explicit latitude/longitude information). In 2019, Twitter has turned off the option of precise georeferencing. Since then georeferenced tweets provide location information usually in terms of places of varying granularity. These coarse georeferences are also user selected, and hence there is no guarantee whether they were posted in that place at all. For this study, however, we rely on the precise georeferences which are system-generated and hence reliable. [24] compared the data from the Streaming API and the Firehose data set (the complete set of tweets available commercially) and stated that the 1% sample provided by the Streaming API almost returns the complete set of precisely georeferenced tweets despite the sampling. The challenge with the small number of precisely georeferenced tweets is that they only represent a set of self-selecting individuals supplying volunteered data. Thus they are highly unlikely to be representative of the entire pedestrian population of the study area. Regardless of this major caveat, it is accepted best practice in the literature to base investigations on this selective data. For this study of predicting pedestrian traffic, even if the tweets are non-representative, the base assumption of a correlation between persons' tweeting and their participation at activities still holds.

2.4 Study settings

The area chosen for this study is the City of Melbourne, one of the 32 local councils making up Greater Melbourne. City of Melbourne covers an area of roughly 37 km² and consists of metropolitan Melbourne's innermost suburbs, including the central business district. The study area includes an area specified by a bounding box, judiciously chosen to cover all sensor locations of the city's pedestrian counting system with adequate buffer zones. The coordinates of the bounding box are (-37.8359, 144.9269, -37.7860, 144.9903).

Since the Twitter dataset contains periods of gaps, this study makes use of the most recent and continuous time span for which the data was collected, from January 2018 to April 2018. Using the bounding box coordinates specified while defining the study area, 28197 precisely georeferenced tweets (a subset of the 10 million tweets extracted by AURIN in Greater Melbourne during the study period) were obtained for the study period. As this study aims to compare and investigate the nature of associations between pedestrian counts (which are relatively large numbers in the study area) and tweet counts (which are comparatively small numbers), any relationship between the two is highly sensitive. To avoid any further bias, we filtered out any consecutive tweets of the same user in our chosen time intervals, hence, counting Twitter users rather than tweets in each 1-hour period. Furthermore, tweeting activity was observed to be anomalous during 1st January and hence, it was removed from the dataset. This resulted in the final dataset of 25679 precisely georeferenced tweets.

3 Correlation analysis between tweet counts and pedestrian counts

The underlying assumption of this experiment is that highly populated outdoor spaces have a greater probability of experiencing high tweet counts, and in turn, high georeferenced tweet counts, than places with lower populations. This is in line with existing literature where social media has been used as proxy measure for urban land use [6], urban activity spaces [19, 23], ambient population [12], and most importantly pedestrian population [34, 7, 4]. While details of these studies [34, 7, 4] have been discussed in Section 1, all of them have assumed the latent existence of an association between tweets and pedestrians. This study bases its hypothesis on such findings and ventures deeper to investigate whether georeferenced Twitter data can actually be used as a viable proxy for inferring pedestrian traffic in an urban area. Since pedestrian count data is the most accurate representation of pedestrian traffic at a given location, this study aims to infer to what extent these counts are correlated with the count of georeferenced tweets. Additionally, this study makes use of vehicular traffic data obtained from SCATS locations to draw comparisons between pedestrian and vehicular travel mode in terms of the strength of correlation. It compares the results of the analyses across the two travel modes to understand whether georeferenced tweets can be inferred as a viable proxy for urban pedestrian traffic.

Using the location information of the active pedestrian sensors, an imaginary circular buffer (catchment) area was drawn with a sensor at the centre of a circle. Similar spatial querying was conducted before by [22] and [15, 16] in their studies of predicting pedestrian volume across intersections in San Francisco and New York City respectively. This spatial querying was performed to capture the number of precisely georeferenced tweets. The radius of the circle was varied from 100 to 1500 metres in steps of 100 metres. Using point-in-polygon analysis, each tweet was assigned to the pedestrian counter(s) in whose catchment area it fell. Correlation was drawn between the observed pedestrian count in each sensor and tweet count inside the catchment area of the same sensor, both at hourly and daily time intervals. For the vehicular traffic data, the SCATS location nearest to each pedestrian sensor was considered as the centre of a catchment circle and correlation was computed for the month of March 2018 only. A sample illustration of the aforementioned method has been shown in Figure 2.

The results of the correlation analysis between georeferenced tweet counts and pedestrian counts are shown in Figure 3. It can be observed that there exists a clear hourly pattern in the variation of correlation coefficient, while the daily pattern is less prominent. The resultant magnitude of correlation coefficients reduces drastically in between 5 AM to 10 AM, while remaining relatively high and statistically significant for the rest of the day. This could be attributed to the fact that Twitter traffic starts increasing more rapidly after 7 AM and reaches its peak quicker than pedestrian traffic, as observed from Twitter data of Melbourne (shown in Figure 4) and Australia [20]. Another possible cause could be that streets that are busy during those times do not cater to a lot of Twitter traffic (pedestrians not tweeting on busy streets before starting work). This indicates that pedestrian activities that are more tweet-productive, are found to be happening before 5 AM and after 10 AM. As far as days of week are concerned, weekends exhibit a slightly improved positive correlation coefficient value than weekdays. This maybe again attributed to the fact that weekend activities (which are more interesting) are more tweet-productive than weekday activities and that tweet counts are more reflective of actual pedestrian counts at places.

Also, the correlation coefficient varies significantly with the radius of the catchment area. It can be observed in Figure 3 that the correlation coefficient gradually increases with the increase in the radius of the circular catchment area, reaching its peak at 500 metres.

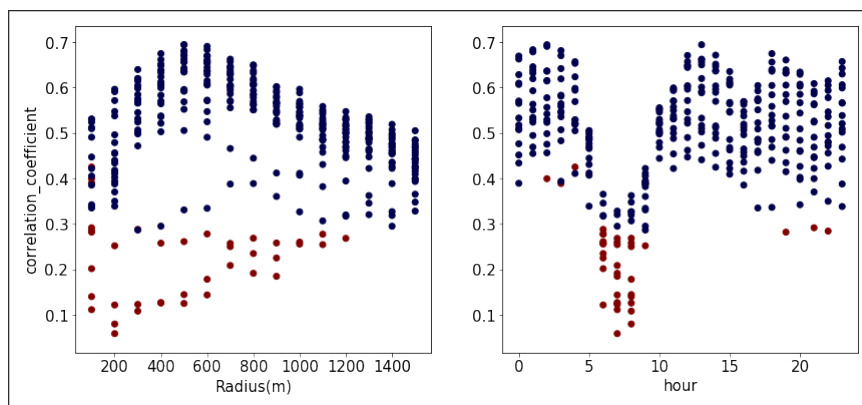


■ **Figure 2** Spatial querying for georeferenced tweets made between 10 AM and 11 AM inside the study area (red triangular markers) using a circular buffer with radius 100, 500 and 1500 metres for a randomly chosen sensor (blue round marker).

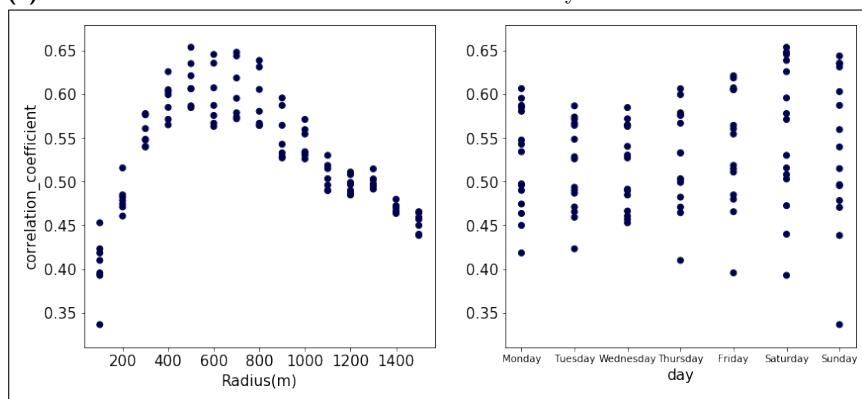
Interestingly, about 500 metres is the average walking range [1, 29, 33, 36, 28]. It then starts to reduce: Larger catchment areas lead to overlaps of catchment areas, and of tweets counted multiple times, thereby reducing the effectiveness of our experiment. The least correlation was observed at 1500 metres radius.

On the other hand, the association between vehicular traffic and georeferenced Twitter traffic appears to be substantially weaker. As shown in Figure 5, the magnitude of the resultant correlation coefficients is relatively less as compared to the ones obtained from pedestrian counts. Also, most of the coefficients are not statistically significant at 95% confidence level. This comparison throws up anticipated and intuitive results. It is more likely that tweets are made during a pedestrian activity as compared to a driving activity as walking is often the final mode of reaching an activity location, from where, presumably, the tweets originate. The results reaffirm this likelihood. Although there exists no binding definition of what a pedestrian activity exactly means (or is limited to), the general consensus is that it usually spans more than just the period of walking itself. On the contrary, vehicular activity is more limited and is confined to only driving a vehicle or being a passenger in one.

While this experiment was aimed more at inferring correlation as opposed to causation (which cannot be proven even with a statistically significant correlation coefficient), it adds the aspect of novelty to this study by establishing the correlation, its magnitude and temporal patterns, before proceeding to use tweets to measure pedestrian activity. Also, explanations can be speculated by observing fair correlations which helps in hypothesis generation. Hence, based on these findings, this study now argues with conviction that georeferenced tweet counts may be used as a viable proxy for estimating pedestrian count under given conditions. The following section aims at calculating errors arising while estimating pedestrian traffic from georeferenced tweet counts.



(a) With radius of catchment circle and hour of the day



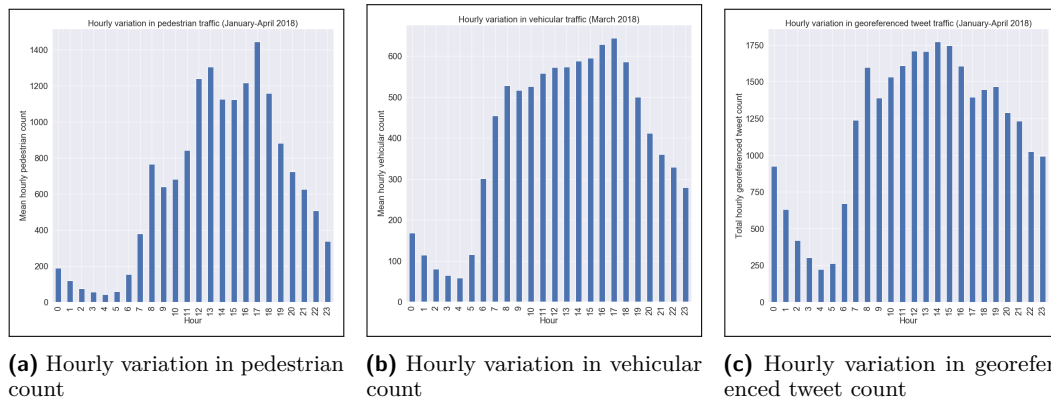
(b) With radius of catchment circle and day of the week

■ **Figure 3** Variation of correlation coefficient (georeferenced tweet counts and pedestrian counts); dark blue points indicate the correlation is statistically significant at 95% confidence level.

4 Estimating pedestrian counts at existing sensor locations

Based on the findings from the first stage of this study, the second stage proposes to use standard regression analysis to estimate pedestrian traffic using tweet counts. It aims to investigate the one-to-one relationship between georeferenced tweet counts and pedestrian counts. It describes, in detail, the methodology of handling the dataset and computing the resultant errors obtained during estimation of pedestrian counts via regression in terms of common regression metrics such as Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The only predictor variable used in regression is precisely georeferenced tweet count.

Using georeferenced tweet counts as the predictor variable (on the x-axis), an attempt was made to replicate its relationship with pedestrian counts, which is the predicted variable (on the y-axis). For this purpose, standard regression modelling was employed. For each hour of each day of the week (e.g., Thursday 1500 hours), a unique regression curve was developed, thus resulting in a total of 168 curves (24 hours multiplied by 7 days). Since this study is the first to investigate such one-to-one relationship between georeferenced tweet counts and pedestrian counts, it was made sure that the chosen regression model is comparatively better (in terms of standard regression metrics) and logical (non-overfitting) at the same time. Hence, trial regression analyses were performed using linear, log-linear, quadratic



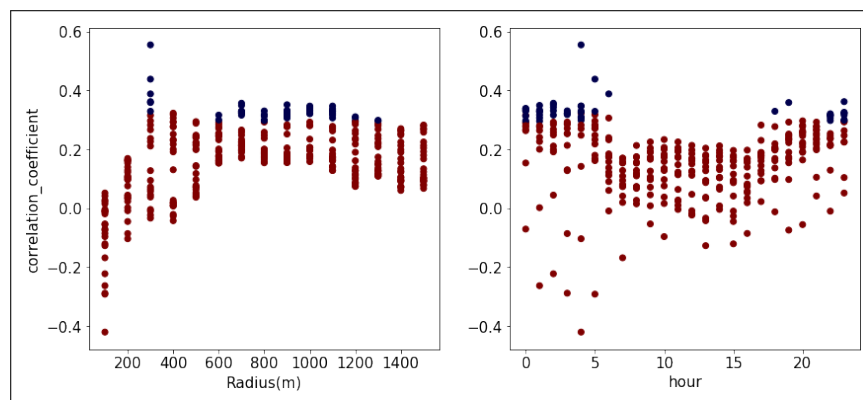
■ **Figure 4** Variation in the City of Melbourne: (a) hourly pedestrian count per sensor, (b) hourly vehicular count per sensor and (c) aggregate hourly tweet count.

and cubic models. Previous studies related to pedestrian count prediction have used either linear or log-linear models to test statistical relationship between walkability measures and pedestrian volume [31, 15, 16]. Although these models have lesser accuracy, these models do not completely contradict this global behaviour, and hence either could be accepted as a viable representation. Quadratic and cubic models exhibited lesser errors but were prone to overfitting, and hence were not considered. The results of the regression analyses are shown in Table 1. Mean hourly values of the regression metrics (R-squared, MAE and MAPE) are obtained by taking arithmetic means of metric values over 168 cases (every hour of every day of the week). The temporal variation of the regression metrics have been shown in Figure 6.

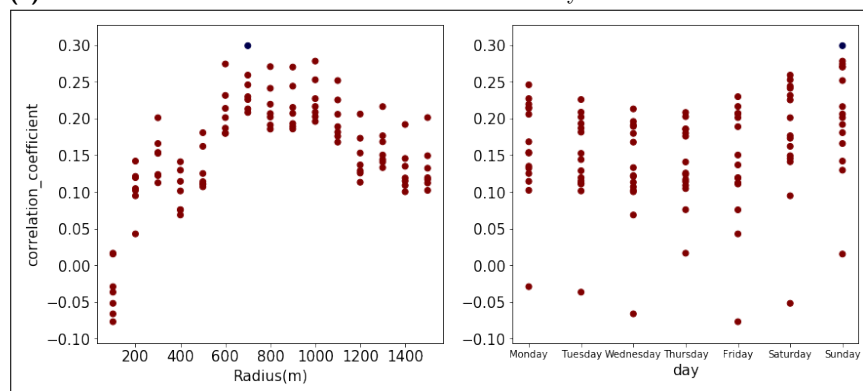
■ **Table 1** Regression metrics for January-April 2018.

Regression model	x-axis	y-axis	Mean hourly R-squared	Mean hourly MAE	Mean hourly MAPE
Linear	Georeferenced tweet count	Pedestrian count	0.426	192.6	28.3
Log-linear	$\log_e(\text{Georeferenced tweet count})$	Pedestrian count	0.424	212.9	26.9

The performance of the *mean hourly tweet count - mean hourly pedestrian count* regression curves obtained from this study were tested by applying the method to predict mean pedestrian counts of a different time period. For this purpose, data from November 2017 was chosen as it was the nearest month available from our study period devoid of known anomalies. They exhibit slightly greater estimation errors (linear: MAE = 274.3, MAPE = 35.83 and log-linear: MAE = 292.0, MAPE = 34.43), which could be due to seasonal variations in the *tweet count - pedestrian count* relationship that was not taken into account due to absence of continuous tweet collection periods. Nevertheless, the errors and temporal patterns are similar to the ones shown in Table 1 and Figure 6 respectively. Hence, the regression curves obtained in this study are acceptable.



(a) With radius of catchment circle and hour of the day



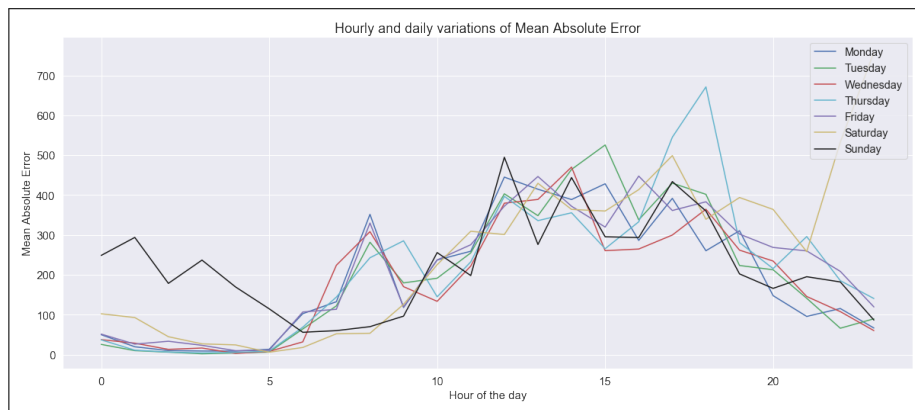
(b) With radius of catchment circle and day of the week

■ **Figure 5** Variation of correlation coefficient (georeferenced tweet counts and vehicular counts); dark blue points indicate the correlation is statistically significant at 95% confidence level.

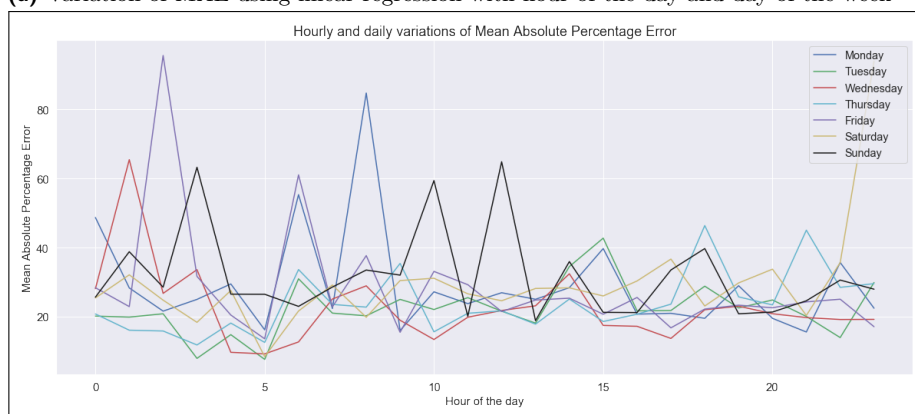
5 Predicting pedestrian counts at locations without any pedestrian count information

The third and final stage of this study is aimed at extrapolation of the developed methodology. The intention to develop a transferable (temporally and spatially) and scalable pedestrian count prediction methodology was based on the motive to predict pedestrian counts at high temporal (hour of the day of the week) and spatial resolution (point on the urban road network), even at locations without any pedestrian count information. The following method helps in predicting the pedestrian counts at any point in an urban pedestrian road network, given the date and time (at hourly granularity).

Pedestrian network data was obtained from OpenStreetMap using the bounding box coordinates specified in Section 2.4. For a given hour of any given date, georeferenced tweets were extracted from the AURIN dataset. Consequently, iterating over all edges of the network, centered on the mid point of an edge spatial querying was conducted using a 500 metre search radius to extract the number of georeferenced tweets. These tweet counts were associated with the corresponding edge. After obtaining the information on the queried hour of the day and day of the week, iterating over all edges of the network, the corresponding regression curve was referred to estimate the pedestrian count passing through an edge. A sample illustration of the spatial querying process to estimate pedestrian counts using georeferenced tweet counts for January 2, 2018 during 1000 to 1100 hours and the resultant estimation of pedestrian counts have been shown in Figure 7.



(a) Variation of MAE using linear regression with hour of the day and day of the week



(b) Variation of MAPE using linear regression with hour of the day and day of the week

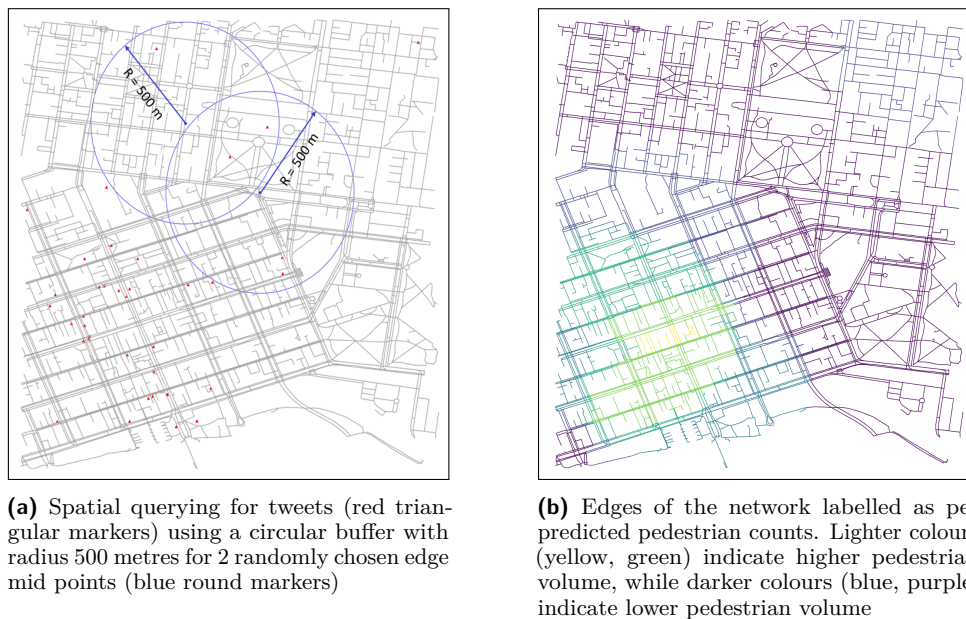
■ **Figure 6** Temporal patterns of regression metrics.

6 Discussion

The three stages of analysis reported in this study makes novel contributions by finding moderate to high correlations between georeferenced tweet counts and pedestrian counts, and then developing a scalable, transferable and non-data-intensive methodology for estimating pedestrian counts from georeferenced tweet counts. Finally, using spatial querying, the study predicted pedestrian counts at high temporal and spatial resolution at locations devoid of sensors. Yet there are limitations of this study that need to be highlighted as well.

First, it was observed in Section 3 that the values of the resultant correlation coefficients during 5 AM to 10 AM were relatively lower in magnitude and statistically insignificant. Hence, predictions using regression curves during this time period are expected to be more erroneous. This is apparent from Figure 6 where the MAE and MAPE can be observed to reach high values (higher than the mean) during this time period, in most of the days. It can be argued that this time period is not ideal for making pedestrian volume prediction using georeferenced tweet counts alone.

Results in Section 4 showed that the proposed methodology produces significant estimation errors in both the study dataset as well as in the testing dataset. While this study argues about the benefits of employing a non-data-intensive approach to predict pedestrian counts in Section 1.2, the magnitude of errors indicate the drawbacks. The regression curve generalises



■ **Figure 7** Prediction of pedestrian counts using precisely georeferenced tweet counts by extrapolation during 1000 to 1100 hours on January 2, 2018.

all network segments with zero georeferenced tweet count as having one and the same pedestrian volume equal to the intercept of the regression curve, which overestimates the actual pedestrian volume in most cases. Furthermore, the betweenness centrality of the edges of the network was calculated to tally the results with the pedestrian count predictions. The dead ends, for example, have zero betweenness centrality but, it can be observed from Figure 7 that the proposed method is not differentiating between through roads and dead ends, in terms of pedestrian counts. These challenges will be addressed in a future study by analysing other network attributes (data-intensive) such as road width, road hierarchy, proximity to transit stops, number of Points-of-Interest which are proven factors known to influence pedestrian demand, to produce more representative results.

The underlying assumption of this study was that the entire study area is homogeneous in terms of every spatial attribute, apart from the spatial distribution of georeferenced tweets. Thus it assumed a existing one-to-one relationship between georeferenced tweet counts and pedestrian counts that varies temporally, but not spatially. The argument in favour of this assumption is that this study was conducted in a relatively homogeneous area in terms of land use. But the results indicate that this assumption is not robust, and there are multiple possible reasons. The relationship between georeferenced tweet counts and pedestrian counts is not independent of spatial variables. Different locations have different tweet count - pedestrian count relationships depending on location type. For example, the tweet productiveness of a railway station is possibly different from the tweet productiveness of an event location, both in magnitude and in temporal patterns. While both may experience pedestrian counts to the same degree, it is expected that an event will bring out greater number of georeferenced tweets than the lesser interesting public transit, for the same number of pedestrian counts. Hence, future work will address this shortcoming by incorporating the spatial variation of the relationship between tweet productivity and land use.

Finally, it must be noted that Twitter has removed the support for precise georeferencing of tweets since June 2019. Thus, the proposed method is applicable only on historic datasets. In terms of estimating pedestrian counts, this move impacts on any real-time interests, but long-term averages should not change quickly. To mitigate this, time-series modelling using historic tweet counts can be applied to predict future tweet counts, which can be used for predicting pedestrian counts using the same principle in future scenarios.

7 Conclusion and future work

Despite the highlighted limitations, this study contributes novel insights. The three-step methodology remains transferable due to use of an omnipresent data source. It can be applied if acceptable correlations are achieved. However, the regression equations in our case study will not hold true for another study area and need to be re-calculated for a different study area. Also, the size of the study area can be increased or decreased without any change in the methodology, with intuitive variations in estimation accuracy. Yet, analysis at micro-level and homogeneous land-use will need some strict assumptions. Also, a study area that is too small will have fewer geotagged tweets. Lastly, we attempted to mitigate population disparity between indoor spaces and adjoining outdoor spaces. We made justifiable assumptions that populated indoor spaces indicate popularity in its adjoining outdoor space, given a space-time buffer. Thus, we placed a 1-hour time buffer and a 500m radius distance buffer around pedestrian counters to capture tweets. We assume to catch most of the tweets and pedestrians in the same buffer although some exceptions will always be there. This uncertainty flattens out as the study area grows in size. Not only does this study investigate the nature of existing correlation, but also proposes an approach to estimate pedestrian counts from georeferenced tweet counts, even at places devoid of pedestrian sensors. By doing so, this study shows the extent to which this non-data-intensive approach can predict pedestrian counts (in terms of estimation errors) and thus brings out the limitations of such an approach, which need to be addressed in future to achieve more accurate and representative results.

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