This Place is Swarming: Using a Mobile Social App to Study Human Traffic in Cities

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***Abstract*—Being a leading location-based social network (LBSN), Foursquare's Swarm app allows users to conduct check-ins at a specified location and share their real-time locations with friends. This app records a massive set of spatio-temporal information of users around the world. In this paper, we track the evolution of user density of the Swarm app in New York City (NYC) for one entire week. We study the temporal patterns of different venue categories, and investigate how the function of venue categories affects the temporal behavior of visitors. Moreover, by applying time-series analysis, we validate that the temporal patterns can be effectively decomposed into regular parts which represent the regular human behavior and stochastic parts which represent the randomness of human behavior. Finally, we build a model to predict the evolution of the user density, and our results demonstrate an accurate prediction.**

***Index Terms*—Mobile Data Sensing, Location Based Social Networks, Spatial and Temporal Analysis, Swarm**

I. Introduction

Due to the rapid development of mobile computing technologies and online social networks (OSNs) [12], mobile social apps, such as Foursquare, Yelp, WhatsApp, and WeChat, are playing a significant role in people's daily-life. Since most of these apps allow users to report and share their real-time locations, they provide us with an opportunity to understand the human mobility at a large scale. Characterizing and forecasting human mobility are important for a number of reasons. First, different types of venues can be better placed to cater for people's requirements. Also, municipal resources can also be more efficiently arranged according to spatio-temporal regularity of human traffic [15] [5]. In addition, users' habit to use these location-based services can be utilized to design better interfaces of mobile apps, and to study richer social interactions [2].

Existing work [13][14] to model mobility characteristics of urban people often utilizes the individual's activity records on LBSNs, which may not be sufficient to track the traffic at a selected venue. Cellular data have also been used to forecast human traffic. However, these backend data are often not publicly accessible. As a popular social app, Swarm's check-in data contain time and location to a fine-grained degree. The data entries that record the major human traffic are real-time and public, providing a new opportunity to track the human trajectories.

In our work, we conduct a data-driven study to understand the human traffic by referring to the spatio-temporal information recorded by a representative mobile social app, so-called Swarm. This app records the number of current visitors at millions of venues all over the world, a.k.a, points of interest (POIs). By collecting the "herenow" data of all venues in New York City (NYC) once per hour for one week, we obtain a set of continuous snapshots, reflecting the real-time geographic distribution of Swarm users in NYC. We aim to extract the temporal patterns of human traffic and study the predictability of the temporal patterns. To the best of our knowledge, we are the first to extract user behavior patterns from the perspective of venues and to study the predictability of venues' traffic. We have made the following three key contributions.

- We track the real-time human traffic of all Swarm venues in NYC by monitoring them at an interval of one hour. We extract various distinctive temporal patterns, which shed light on studying user behavior from venues' perspective.
- We further analyze the temporal traffic patterns, and validate that venue traffic can be well decomposed of regular parts that represent the periodicity of human mobility and stochastic parts that represent the randomness.
- Based on the decomposition results, we predict the regular parts of the temporal patterns accurately using historical traffic data.

The rest of the paper is organized as follows. Section II describes our data and collection method. In Section III, we show the temporal patterns of different venue categories. In Section IV, we explore the possibility of decomposing the temporal patterns into regular parts and random parts. In Section V, we build a model to predict the user density based on the historical data and use real traces to validate the accuracy of our model. In Section VI, we discuss the related work. Finally, we conclude our work and discuss some future work.

II. Background and Data Collection

A. The Swarm App

As a leading location-based social networking service, Foursquare has attracted more than 50 million active users

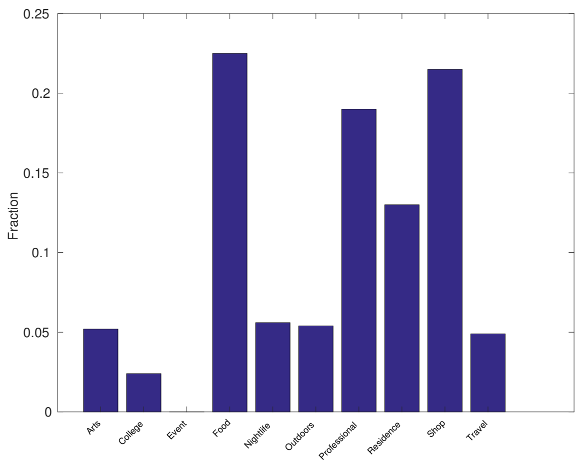


Fig. 1: The Category Distribution of Venues by their numbers in NYC.

per month [1]. Since May 2014, Foursquare has been split into two apps, i.e., Foursquare City Guide and Foursquare Swarm. Using the Swarm app, users can conduct check-ins to publish their real-time locations [6]. By August 2015, Swarm has recorded the location history of more than 60 million users [2]. To preserve the user privacy, Swarm makes a user's spatial and temporal information visible to her friends only. Meanwhile, from a venue's perspective, Swarm only makes some aggregated information available to the public, such as how many users have visited the venue, how many check-ins have been conducted at the venue until now, and how many visitors are around the venue currently.

B. Data Collection

Our data collection has two parts. The first is to collect the venues' static profiles. In addition, for each venue, we track the "herenow" attribute from time to time, which reflects the number of users around the venue at the moment. A "venue" in the Swarm app represents a point of interest (POI). Each venue in Swarm has a numeric ID. When conducting a check-in via Swarm, a venue must be specified.

By using the location-based search function, we are able to obtain all venue IDs within NYC. Excluding the venues with no tips, we get 60,844 venue IDs in NYC. We first fetch the static profiles of all these venues, including their names, categories, geo-locations, and total number of check-ins, by conducting the crawling from February 28, 2016 to March 5, 2016. The distributed data crawling system was developed based on the method proposed in [7]. We launched 60 virtual machines from the "East US" data center of the Microsoft Azure platform. Each virtual machine has an independent IP address and runs a dedicated crawler. All 60 crawlers work together to fetch data in a collaborative way.

We then tracked the "herenow" counts of these venues over one week. In particular, the "herenow" count of a venue is a non-negative number, indicating the number of people who have conducted a check-in within the latest three hours. Each check-in is counted into the "herenow" at this venue under the condition that the user conducts no check-ins further at other venues since then. Therefore, the "herenow" count can represent the up-to-date number of Swarm users at this venue. Note that only a user's latest check-in will be taken into account to avoid duplication. By aggregating the "herenow" count of all the venues in a city, we can obtain the distribution of Swarm users at a certain moment. From October 24, 2016 to October 31, 2016, we collected the "herenow" count of each venue in NYC per hour. Finally we obtained 168 continuous snapshots of "herenow" numbers of all venues in NYC during one entire week.

III. Visualization of Temporal Human Traffic

Venues in Swarm are divided into 10 typical categories. Fig. 1 shows the distribution of venues in NYC by their numbers over the 10 categories. From this figure, we find that venues in "Event" category take up less than 1%, thus we do not consider this category in the following analysis. Based on the "herenow" counts, Fig. 2 shows the temporal patterns at venues of different categories. From the figures, we obtain the following findings.

1) People prefer to use Swarm for entertainment: We assume venues belonging to "Food", "Arts", "Nightlife", "Outdoors" and "Shop" as the entertainment venues. We observe that people tend to check-in at these entertainment venues than others. From Fig. 2, both the peak and average "herenow" numbers in these venues are much higher than the ones in other categories. Besides, the "herenow" count is not exactly proportional to the category distribution of venues. "Arts" venues take up about 5 percent of the total venues, but their "herenow" counts are higher than those of "Residence" category whose number of venues are almost three times as "Arts". The "herenow" counts of "Travel" are also much lower than those of "Arts", although they take up the same proportion. Popularity of the venue categories is an important reason for the disparity.

2) Different types of venues have different temporal patterns: From the view of one day, some venues are popular at a certain time of the day, thus the traffic patterns there only have one peak. For example, "Arts" places have a peak at night, which means at that time, people have free time to visit such venues. Some venues are popular at two moments a day. "Travel" is a typical two-time-peaked category. It is because people will check-in when they go out in the morning and come back in the afternoon. From a week's perspective, venues' temporal pattern also changes a lot. "Nightlife" venues become more and more popular from Monday to Saturday and reach a peak at Saturday night. This is because when weekend approaches, people tend to have more free time to hang out through the evenings, and they can have a good rest on Sunday. There are fewer "Nightlife" activities during Sunday evenings as most of the users have to work from Monday. For "Professional" venues, there are many more visitors during weekdays than weekends, since people often do not go to

[1] https://foursquare.com/about, accessed in October 2016

[2] https://https://venturebeat.com/2015/08/18/foursquare-by-the-numbers-60m-registered-users-50m-maus-and-75m-tips-to-date/

Category	Venues	Interpretation
Food	Breakfast Spot, Restaurant	Peaks during lunch/dinner slots on weekends; popular during the daytime on weekends
College	College Academic Building, Student Center	Few visitors during the weekend
Arts	Art Gallery, Movie Theater, Stadium	More visitors in the afternoon during the weekdays
Nightlife	Bar, Nightclub, Pub	More visitors during Friday and Saturday evenings
Outdoors	Golf Course, Forest, Garden	More visitors in mornings and afternoons on weekdays; more visitors in the daytime during the weekends
Professional	Office, Medical Center, Government Building	More visitors in the mornings during weekdays; fewer visitors during weekends
Residence	Home, Residential Building	More visitors in the evenings
Shop	Clothing Store, Food & Drink Shop	A peak on Saturday, more visitors on Friday to Sunday
Travel	Airport, Bus Stop, Subway	More visitors in mornings and afternoons during weekdays; popular for the whole day during weekdays

TABLE I: Features of Different Venue Categories in NYC

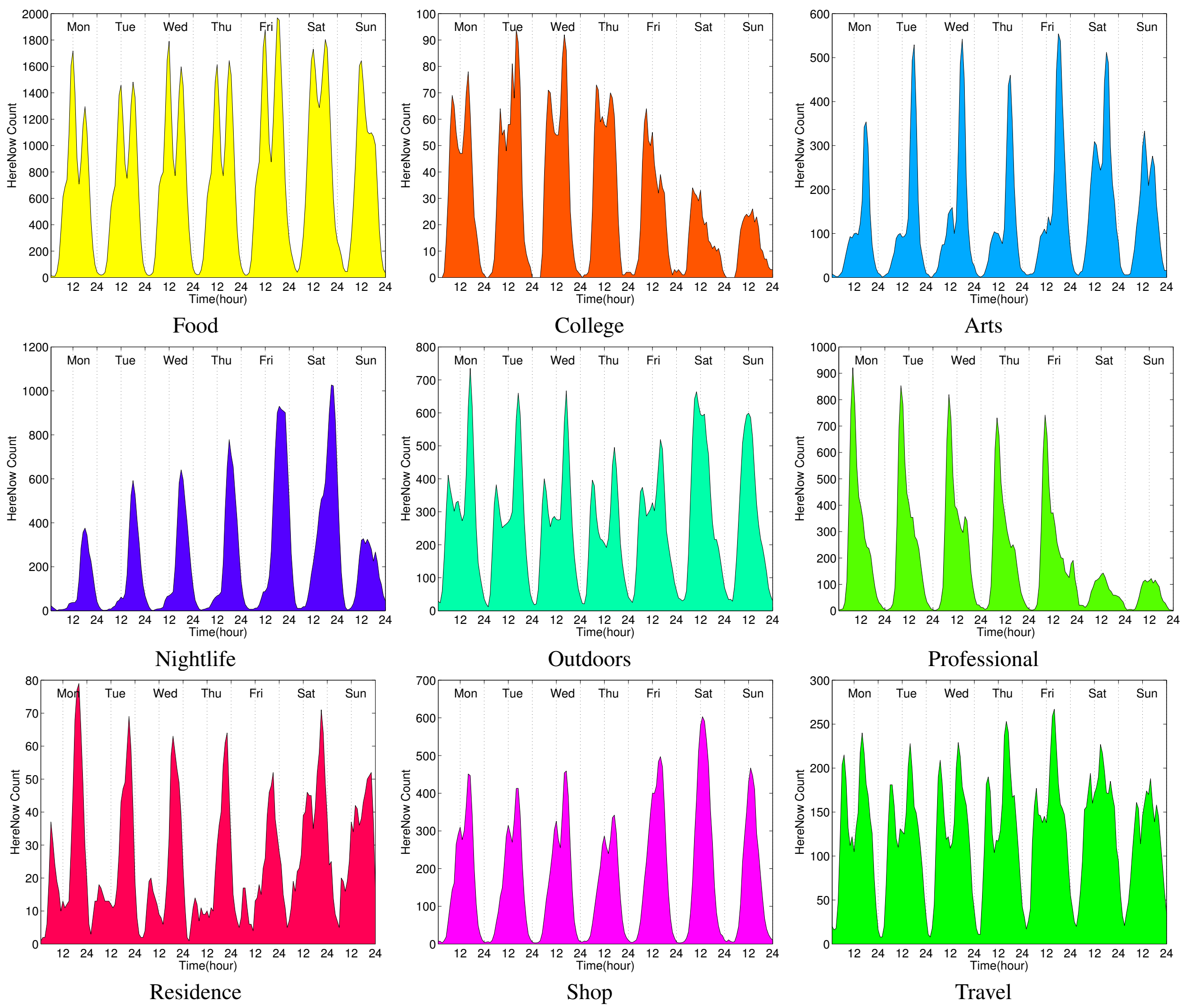


Fig. 2: Temporal Patterns of Different Categories of Venues in NYC

work during weekends. Temporal features of each category are summarized in Table I.

IV. Human Traffic Decomposition

In the previous section, we have visualized the temporal patterns of human traffic at nine main categories of venues. In this section, we further explore how the traffic patterns form and what they are composed of. We apply the classical time series decomposition method [4] to the traffic sequence at venues, trying to deduce human traffic characteristics. In special, we observe from Fig. 2 that patterns at weekends are different from that on weekdays. This is in accord with people's working rhythm. In our study, we focus on the analysis about human traffic on weekdays.

Based on the classical time series decomposition theory, for any time-changing sequence, its evolution can be regarded as composed by three components: general tendency, periodic part, and stochastic ingredient. Moreover, the former two components are considered together as the regular part while the stochastic component is considered as the stochastic part. Considering the temporal traffic pattern at venues, it should consist of general and periodic parts, while some random factors like extreme weather or special events, may also affect a venue's traffic stochastically. From Fig. 2 we observe that the patterns of human traffic at venues show strong regular variations as well as noticeable randomness. Therefore, we decide to decompose a "herenow" series into regular part and stochastic part.

Given a temporal traffic pattern P^i at a venue i, the venue's "herenow" series can be represented by $Y^i = \{y_1^i, y_2^i, ..., y_t^i, ...y_N^i\}$, where y_t^i is the "herenow" number at the t-th hour, and N is the number of the snapshots we have got ($N = 168$). y_t^i can be denoted as the sum of a general trend T_t^i, a periodic part S_t^i, and a stochastic part I_t^i, i.e., we have $y_t^i = T_t^i + S_t^i + I_t^i$. The general trend T_t^i and periodic part S_t^i compose the regular part of a time series, i.e., we have $R_t^i = T_t^i + S_t^i$. Given a time series traffic pattern at a venue, our aim is to derive the regular and stochastic components. The detailed steps of decomposition are described in Algorithm 1.

We choose a department store belonging to the "Food" category, so-called Macy's, located in the Garment District of NYC as an example for illustration. Fig. 3 shows the decomposition result of the human traffic from Monday to Friday at this venue. Fig. 3(a) and Fig. 3(b) show the regular component and stochastic component of the time series traffic pattern at the selected venue. It can be observed from these two sub figures that the regular component of the traffic pattern shows a strong periodicity, while the stochastic component shows great irregularity.

To verify the effectiveness of our decomposition method, we use the autocorrelation function(ACF) [3] to test the interdependence of a time sequence. Given a time sequence $Y = \{y_1, y_2, ..., y_t, ...y_N\}$, its lag k autocorrelation function ACF_k is is defined as Equation (4)

$$ACF_k = \frac{\sum_{i=1}^{N-k}(y_i - \overline{Y})(y_{i+k} - \overline{Y}))}{\sum_{i=1}^{N}(y_i - \overline{Y})^2} \tag{4}$$

Algorithm 1 Time series decomposition of a venue's "herenow" series

Input: A pattern's "herenow" time series $Y = \{y_1, y_2, ...y_N\}$

Output: General trend T_t; Periodic part S_t; Stochastic part I_t; Regular part R_t;

1: Applying a moving average filter to firstly estimate a rough general trend. For "herenow" count y_t at each time t, moving average g_t can be calculated as formula (1).

$$g_t = (0.5y_{t-p} + y_{t-p+1} + ... + y_{t+p-1} + 0.5y_{t+p})/d, \quad p < t < n-p, \; p = d/2 \tag{1}$$

d is the moving average filter's time window size we set.

2: Computing the average w_k of deviation$\{y_{k+id} - g_{k+id}\}, p < k + id < n - p, k = 1, 2, 3..., d$

3: Computing the periodic part S_t by formula (2).

$$S_t = \begin{cases} w_t - \sum\limits_{i=1}^{d} w_i/d, & 1 <= t <= d \\ S_{t-d}, & d < t <= N \end{cases} \tag{2}$$

the remaining part r_t is computed as $r_t = y_t - S_t$

4: Applying a moving filter on r_t to obtain a better general trend T_t. For $t < 1, y_t = y_1; t > N, y_t = y_N$.

$$T_t = (r_{t-p} + r_{t-p+1} + ... + r_{t+p-1} + r_{t+p})/d, \quad 1 <= t <= N \tag{3}$$

5: Computing I_t by $T_t = y_t - T_t - S_t$ and $R_t = T_t + S_t$

6: **return** T_t,S_t,I_t,R_t;

$\overline{Y}$ is the mean of the time sequence Y. The blue lines in Fig. 3(c) and Fig. 3(d) are the bounds with value of $\pm 1.96/\sqrt{N}$. If a time series is a random sequence, then more than 95% of its autocorrelations should fall between these blue lines [4]. We observe that the regular component shows regularities, as its autocorrelations are beyond bonds in Fig. 3(c). The autocorrelations of stochastic part follows the random rule with the autocorrelations falling inside the bonds in Fig. 3(d). Therefore, this venue's "herenow" sequence is decomposed into regular and stochastic parts effectively.

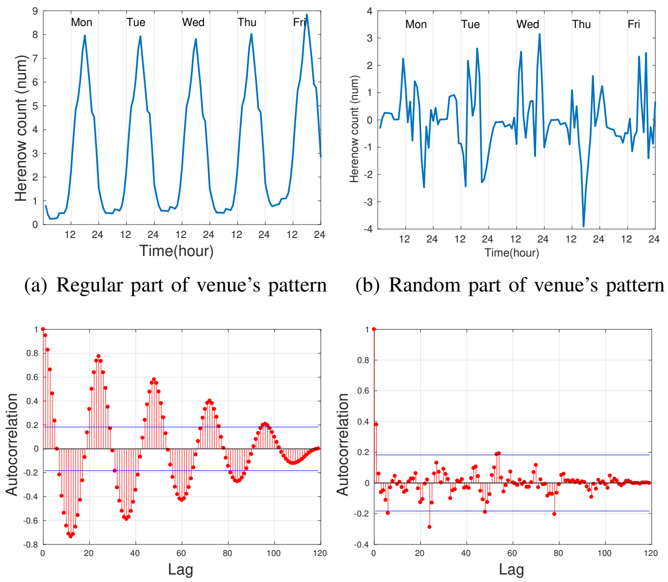
We apply this classical time series decomposition method to the "herenow" series of all the venues in NYC. Results are shown in Table II. The autocorrelations of stochastic parts by various time lags are very small, which means the interdependences in these stochastic parts are weak. So these patterns of almost all venues in NYC are effectively decomposed by this method. In summary, we validate that the temporal patterns of traffic of a venue in Swarm can be decomposed into regular part and stochastic part by applying the classical time series decomposition method.

V. Prediction of Human Traffic Patterns

Knowing human traffic patterns is of great benefit to venue managers to better cope with different tourists flow. Governments can also schedule transportation traffic better if the real-time traffic at geographical venues can be correctly predicted in advance. After fully analyzing the human traffic at venues

Category	Lag=12	Lag=36	Lag=60	Lag=84
Arts	-0.0850	0.0363	0.0300	0.0202
College	-0.0506	0.0421	0.0152	0.0102
Food	-0.0638	0.0356	0.0220	0.0116
Nightlife	-0.0739	0.0297	0.0258	0.0249
Outdoors	-0.0471	0.0295	0.0111	0.0097
Professional	-0.0616	0.0394	0.0261	0.0032
Residence	-0.0450	0.0223	0.0256	0.0249
Shops	-0.0582	0.0362	0.0148	0.0099
Travel	-0.0635	0.0299	0.0094	0.0165
ALL	-0.0610	0.0334	0.0200	0.0145

TABLE II: Mean autocorrelations of stochastic parts of venues in different categories



(a) Regular part of venue's pattern (b) Random part of venue's pattern

(c) Autocorrelation of regular part (d) Autocorrelation of stochastic part

Fig. 3: The decomposition result of a Foursquare venue (Macy's in the Garment District of NYC)

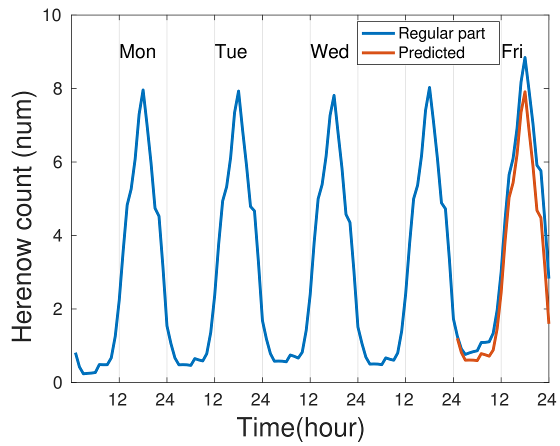


Fig. 4: Result of a venue's regular part of "herenow" sequence prediction

	AR1	SAR1	MA1	MA2	MA3	SMA1
	0.991	-0.837	0.521	-0.085	0.233	-0.456
s.e.	0.013	0.095	0.070	0.075	0.099	0.153

TABLE III: Parameters of a venue's prediction

by decomposition, it is possible to predict the traffic patterns at venues.

In this subsection, we utilize the seasonal Autoregressive Integrated Moving Average (ARIMA) model [8] to predict the sequential traffic at venues. As the time series traffics can be decomposed into regular and stochastic parts effectively, we first predict the regular component of the time series traffic pattern, and then apply the prediction to the original temporal patterns of the venues. We compare these two results.

A seasonal ARIMA model is an extension of an ARIMA model by adding seasonal terms. It not only considers the general trend and periodicity for one day, but also integrates seasonal components that repeat every s observations of the series [8]. It can be written as $ARIMA\ (p, d, q) \times (P, D, Q)_s$. Here (p, d, q) represents the non-seasonal part of the model, while $(P, D, Q)_s$ denotes the seasonal part of the model. Precisely, p is the number of nonseasonal autoregressive (AR) terms, d is the the number of nonseasonal difference terms, q is the number of nonseasonal moving average (MA) terms, while P, D, Q are the corresponding numbers of seasonal terms. s specifies the number of periods in a season.

We use the "herenow" data from Monday to Thursday to train the model. Our goal is to predict the number of "herenow" of each hour on Friday. We apply non-seasonal differencing d times to remove general trend, and then utilize seasonal differencing D times to remove seasonal trend. Finally we get a stationary "herenow" series. We use the partial autocorrelation function (PACF) to decide p and P terms; after that, we use the Akaike information criterion (AIC)[1] to decide q and Q. Fig 4 shows the prediction results of regular part of "herenow" sequence for the selected venue. We observe that the predicted data fits the regular part of the real data well. The parameters used for this example are listed in Table III.

We train and test similar models for the traffic series of all the venues in NYC. To evaluate our prediction result quantitatively, we utilize the relative error. It is defined by Equation (5).

$$relative\ error = \frac{|x_{true} - x_{predict}|}{|x_{true}| + \epsilon} \tag{5}$$

We extend the technique to predict the original time sequence of all venues in NYC. Table IV shows the proportion of venues whose prediction relative error is less than 0.15 and 0.3, for the regular and original sequences respectively. While hardly a venue's original data can be predicted with less than

Category	Regular (0.15)	Original (0.15)	Regular (0.3)	Original (0.3)
Arts	81.65	3.67	94.5	35.78
College	88.46	7.69	96.15	30.77
Food	92.79	9.22	99.50	50.90
Nightlife	87.33	3.67	99.00	46.33
Outdoors	89.46	2.38	98.64	26.19
Professional	81.40	10.74	98.35	52.48
Residence	88.89	5.25	94.44	44.44
Shops	89.74	4.27	99.15	36.75
Travel	77.69	2.31	97.69	25.48
Average	86.38	5.47	97.49	44.07

TABLE IV: Proportion of relative error less than 0.15 and 0.30 of both predictions

0.15 relative errors, the prediction for its regular part is high, about 86% are with relative error values less than 0.15. On the other hand, when relative errors come to 0.3, nearly 97% of regular temporal patterns follow the rule while about 44% of original data are predicted with less than 0.3 relative error.

These pairs of results first show that prediction of regular part is more precise, which means the decomposition procedure is necessary and effective. We also infer that it is the stochastic part of the original data that cause it hard to predict them with small relative errors. Finally, this validates the hypothesis that most venues' "herenow" sequences can be predicted by historical data.

VI. Related Work

LBSNs have been popular for years. Massive user trajectories are generated on LBSNs since most of them have corresponding mobile apps. Many works have been done based on these trajectories to study human activity. Hu et al. [10] explored users' check-in timespan patterns in Foursquare within a day. Preoţiuc-Pietro et al. [14] selected two categories of venues to observe their one month check-in patterns. Both of them only considered users who pushed their check-ins on public social networks, especially Twitter. We observe the check-in records of all the venues in NYC in a whole week.

Based on the analysis on the human traffic distribution, human activity forecasting becomes possible. Huang et al. [11] utilized an image processing method to predict the dynamics of human interaction. Noulas et al. [13] proposed two models to predict a user's next visiting location in Foursquare. These forecasts are motivated for individuals. Xu et al. [16] applied time series prediction to the cellular data in China. Ghosh et al. [9] utilized a Bayesian time series model to predict the city traffic of Dublin. Our work is inspired by their research to explore the application of time series analysis to LBSN problems. Our forecast is from the angle of venue, focusing on venues' temporal traffic patterns.

VII. Conclusion and Discussions

By referring to the real-time data of the Swarm app, we use the temporal information of massive users to study human traffic in cities. We develop a distributed web crawler which is able to monitor any venue in NYC at one hour's interval. We utilize the "herenow" data of Swarm we crawled to extract several human behavior patterns and generalize their features. We further validate that the human traffic patterns compose regular and stochastic parts by applying the classical time series decomposition to the "herenow" series of venues in NYC. After that, we build a seasonal ARIMA model and validate that the regular part of these temporal patterns can be well predicted by historical data.

There are still quite a lot to explore about human traffic in cities. We will further explore the decomposed stochastic part in order to know more about unexpected human traffics, taking random factors into consideration such as extreme weather, air quality and special events. We aim to build a more accurate model for human traffic prediction.

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References

[1] H. Akaike. Akaikes information criterion. In *International Encyclopedia of Statistical Science*, pages 25–25. Springer, 2011.

[2] F. Benevenuto, T. Rodrigues, M. Cha, and V. Almeida. Characterizing User Behavior in Online Social Networks. In *Proc. of ACM SIGCOMM*, 2009.

[3] G. E. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung. *Time series analysis: forecasting and control*. John Wiley & Sons, 2015.

[4] P. J. Brockwell and R. A. Davis. *Introduction to time series and forecasting*. springer, 2016.

[5] E. R. Burrell, H. A. Pines, E. Robbie, L. Coleman, R. D. Murphy, K. L. Hess, P. Anton, and P. M. Gorbach. Use of the Location-based Social Networking Application GRINDR as a Recruitment Tool in Rectal Microbicide Development Research. *AIDS and Behavior*, 16(7):1816–1820, 2012.

[6] Y. Chen, J. Hu, H. Zhao, Y. Xiao, and P. Hui. Measurement and Analysis of the Swarm Social Network with Tens of Millions of Nodes. *IEEE Access*, 2018.

[7] Y. Chen, Y. Yang, J. Hu, and C. Zhuang. Measurement and Analysis of Tips in Foursquare. In *Proc. of IEEE PerCom Workshops*, 2016.

[8] M. Gerolimetto. ARIMA and SARIMA models. *CaFoscari University of Venice, Italy*, 2010.

[9] B. Ghosh, B. Basu, and M. O'Mahony. Bayesian Time-Series Model for Short-Term Traffic Flow Forecasting. *Journal of Transportation Engineering*, 133(3):180–189, 2007.

[10] T. Hu, E. Bigelow, J. Luo, and H. Kautz. Tales of Two Cities: Using Social Media to Understand Idiosyncratic Lifestyles in Distinctive Metropolitan Areas. *IEEE Transactions on Big Data*, 3(1):55–66, 2017.

[11] D.-A. Huang and K. M. Kitani. Action-Reaction: Forecasting the Dynamics of Human Interaction. In *Proc. of ECCV*, 2014.

[12] L. Jin, Y. Chen, T. Wang, P. Hui, and A. V. Vasilakos. Understanding User Behavior in Online Social Networks: A Survey. *Communications Magazine, IEEE*, 51(9):144–150, 2013.

[13] A. Noulas, S. Scellato, N. Lathia, and C. Mascolo. Mining User Mobility Features for Next Place Prediction in Location-based Services. In *Proc. of ICDM*. IEEE, 2012.

[14] D. Preoţiuc-Pietro and T. Cohn. Mining User Behaviours: A Study of Check-in Patterns in Location Based Social Networks. In *Proc. of ACM WebSci*, 2013.

[15] C. Ratti, D. Frenchman, R. M. Pulselli, and S. Williams. Mobile Landscapes: Using Location Data from Cell Phones for Urban Analysis. *Environment and Planning B: Planning and Design*, 33(5):727–748, 2006.

[16] F. Xu, Y. Lin, J. Huang, D. Wu, H. Shi, J. Song, and Y. Li. Big Data Driven Mobile Traffic Understanding and Forecasting: A Time Series Approach. *IEEE Transactions on Services Computing*, 9(5):796–805, 2016.