Analytical Framework in Cloud-Native Environments for Auto-Modelling Sparse Human Mobility Considering Memory of Past Contexts

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***Abstract*— Understanding human mobility is linked to the dynamics of humans' complex decision-making but is a critical component in modern applications, ranging from business strategies in supermarkets to the common good amid pandemic crises. Meanwhile, massive data brought by the increasing availability of trajectory recordings and emerging machine learning techniques have led to better trajectory modelling in recent studies. Many approaches have been then proposed to explain the modelling of complex human mobility. Nevertheless, the interaction between a suite of machine learning algorithms and feature impacts has not been completely explored in terms of the memory of past contexts by state-of-the-art works. Moreover, many existing studies have only discussed theories although their feasibility should be tested out in modern application environments and is also important from the view of open access to the proposed framework. This study attempts to fill this gap by proposing an analytical framework which fits modern (cloud-native) settings and elucidating the interplay between metrics and various parameters to help understand mobility in more detail. As a result, the proposed framework has illuminated marked differences among various machine learning algorithms, feature impacts, and metrics given the memory of past contextual information. This study catered for insights that customer mobility has been best predicted by backpropagating some recent nodes information in a supermarket case study and that feature impacts do not necessarily come along with the coherence to all machine learning algorithms.**

Keywords—Human Mobility, Trajectory Modelling, Machine Learning, Cloud-Native, Geo AI

I. Introduction

Understanding human mobility is linked to the dynamics of humans' complex decision-making but is a critical component in modern applications, ranging from public health [1], smart city concepts [2], energy efficiency [3], traffic jams [4], disaster displacement [5], and infection transmission [6]. Especially in a supermarket scenario, collecting customer shopping path data is directly connected to better capturing the detailed grasp of their purchase decision process than just with Point-Of-Sales (POS; customer transaction logs) data [7].

In recent studies, massive data brought by the increasing availability of trajectory recordings such as GPS [8][9], cellular information [10][11], and Bluetooth [12], and emerging machine learning techniques have led to better human modelling. A variety of modelling methods have been recently developed for this purpose to capture human mobility [13][14][15][16].

Nevertheless, the interaction between a suite of machine learning algorithms and feature impacts has not been methodically explored in terms of the memory of past contexts by state-of-the-art works. Moreover, many existing studies have only discussed theories although their feasibility should be tested out in modern application environments and is also important from the view of open access to the proposed framework.

This study attempts to fill this gap by proposing an analytical framework which fits modern (cloud-native) settings and elucidating the interplay between metrics and various parameters to help understand mobility in more detail.

II. Related Work

A. Customer Behaviour Modelling

Many studies have been devoted to grasping customer needs and expectations. Making full use of a POS system can help supermarkets listen to their customers and optimise their back-office operations e.g. recommendations [17]. From an industry view, there are solution areas to support these demands: AI in Retail[1], Azure for Retail[2], and AWS Retail[3]. POS data are, however, simply records of purchase history and are not detailed enough to represent their decision-making process. [7]. This aspect is also lethal to the optimisation of supermarket layouts. Another approach is to leverage customer movements. Shopping path data used to be gathered manually for this purpose [18], but recent developments in radio wave technologies established solid ways to automatically track customer movements in a store. The customer movements are then analysed to cater for mobility insights from the view of spatiotemporal aspects.

[1] AI in Retail: https://www.microsoft.com/en-us/ai/industry/ai-in-retail
[2] Azure for Retail: https://azure.microsoft.com/en-us/solutions/industries/retailers/#overview
[3] AWS Retail: https://aws.amazon.com/retail/

B. *Human Mobility Modelling*

The current approach to predicting human mobility assumes that an individual tends to follow the inclination of crowd movements [19], for instance, in a mall [20]. Studies considering this prediction strategy using machine learning algorithms such as the Bayes theorem [21], tree-based model [22], the Markov theorem [20][23][24], and neural networks [25] have been extensively investigated while segmenting zones as nodes [26]. Although state-of-the-art works demonstrated the accuracy of around 50% as huge multi-class classification problems, there has not been a comprehensive study on various machine learning algorithms, feature impacts, and variations by the memory (referred to as look-back, hereafter) of past contextual information. In this way, a baseline in this study refers to a performance when the look-back is set to one. Also, this study mainly focuses on the variation by the lookback in vanilla machine learning architectures but the accuracy itself compared to the exiting studies. In addition, conventional studies proposed theories but rarely validated the feasibility in modern application environments i.e. effective use of the scalable computation power. It is also considered important to provide an open access to the proposed framework.

III. METHODS

This study proposes the combination of an analytical framework which consists of step-by-step data processing and a cloud architecture where the framework is incorporated.

A. *Analytical Framework*

Fig. 1 describes the overall analytical framework.

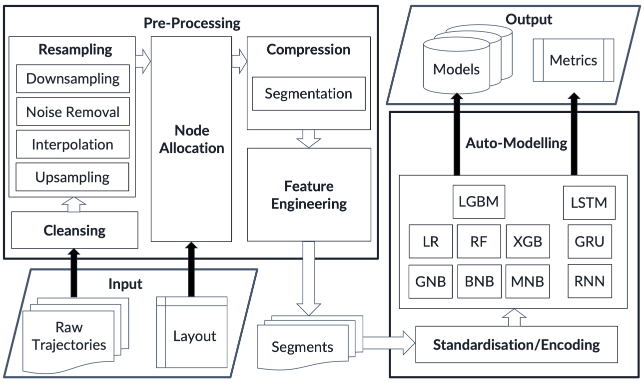

Fig. 1. Analytical framework.

The analytical framework is comprised of two major parts: pre-processing and auto-modelling. The former part is for cleansing and filtering noisy trajectories which possibly can affect models' quality whereas the latter part is for auto-modelling human mobility – predicting the next location of human movements by a suite of machine learning algorithms based on various features and the look-back of past contextual information, that is, the length of the look-back period.

B. *Pre-Processing*

As depicted in Fig. 1, raw trajectories are resampled to certain intervals as shown in Fig. 2 since the frequency is not consistent in most datasets.

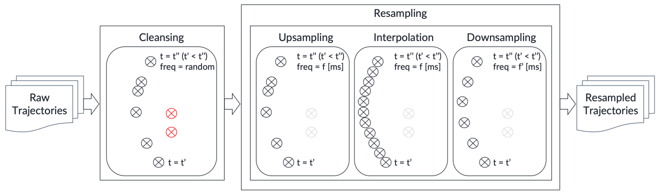

Fig. 2. Resampling procedure.

For interpolations within the resampling procedure, linear interpolation is employed because Runge's phenomenon is less observed in spatial scenarios compared to other interpolation methods as shown in Fig. 3. Resampled trajectories are then transformed into segments, which are inputs to auto-modelling.

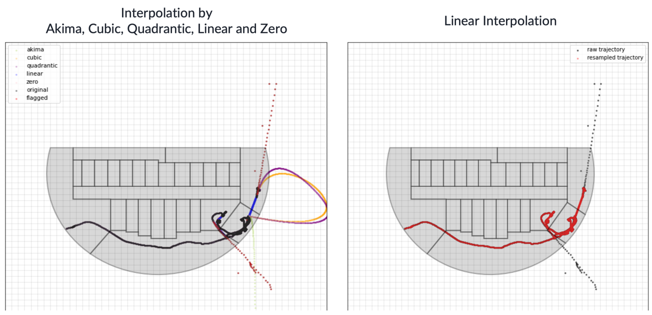

Fig 3. Results of linear interpolation on certain trajectory compared to various interpolations.

C. *Auto-Modelling*

Auto-modelling consists of various machine learning algorithms ranging from conventional to recent ones, but each algorithm is based on vanilla architecture to prove the generality of the proposed framework. Auto-modelling contains the following algorithms: Logistic Regression (LR), Gaussian Naive Bayes (GNB), Bernoulli Naive Bayes (BNB), Multinominal Naive Bayes (MNB), Random Forest (RF), XGBoost (XGB), LightGBM (LGBM), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU).

Methods based on neural networks shown in Fig. 4 uses the following vanilla architecture: RNN/LSTM/GRU layer (112 dimensions), two ReLU activation layer with L2 regularisation, SoftMax activation layer to output the probability for each node i.e. zone information at the end, and a dropout layer is set every layer in between. Note that the final dimension is identical to the number of unique nodes. The networks are trained with Adam optimiser with accuracy as its metric, and the validation loss is monitored to reduce the learning rate (by 0.5) by the patience of five steps and stop training by the patience of 10. 20% of the whole dataset is used for testing purpose, and the remaining dataset is split into training (80%) and validation (20%).

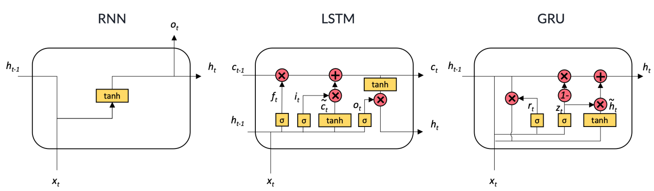

Fig 4. Schematic architecture of neural network algorithms where c_t, x_t, h_t, o_t, f_t, i_t, z_t, and r_t denote cell state (context vector), input vector, hidden layer vector, output vector, forget gate vector, input gate vector, update gate vector, and reset vector, respectively.

D. Cloud-Native Application Architecture

The framework is doe in Python 3 (ver. Anaconda3-5.3.1) with Keras (ver. 2.8.0) and Scikit-Learn (ver. 0.19.2) libraries. It is then deployed in cloud-native application architecture for securing scalable computation power and open access to the proposed framework as shown in Fig. 5.

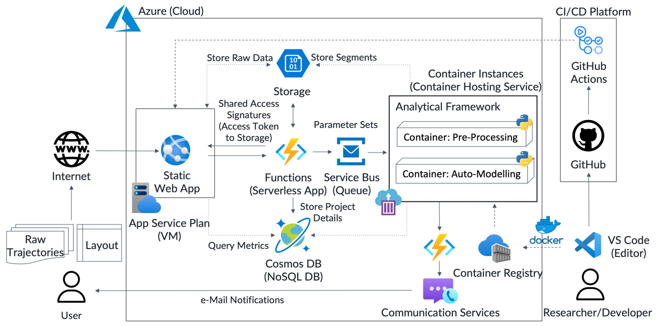

Fig. 5. Analytical framework in cloud-native application architecture.

There are two types of inputs: inputs to the application (pre-processing) and inputs to auto-modelling. The former refers to a layout file in a JSON format and a trajectory dataset where each record contains a user ID, x, y, and timestamp. The latter refers to segments with features being engineered contain user ID, node information, stay time, travel distance, mean heading, max velocity, mean velocity, median velocity, variance velocity, max acceleration, mean acceleration, median acceleration, and variance acceleration.

IV. Results

This section introduces the dataset used for the validation of the proposed framework along with its architecture and description. A particular focus is given to the comparative evaluation of results among different machine learning methods and the baseline.

A. Data

As a part of case studies, the proposed framework is applied to a trajectory dataset gathered from a supermarket at Tsinghua University in Beijing, China. The dataset is collected using an ultra-wideband indoor positioning system, and it contains sparse and noisy records. A floor of the supermarket is categorised into 28 different zones as shown in Fig. 6.

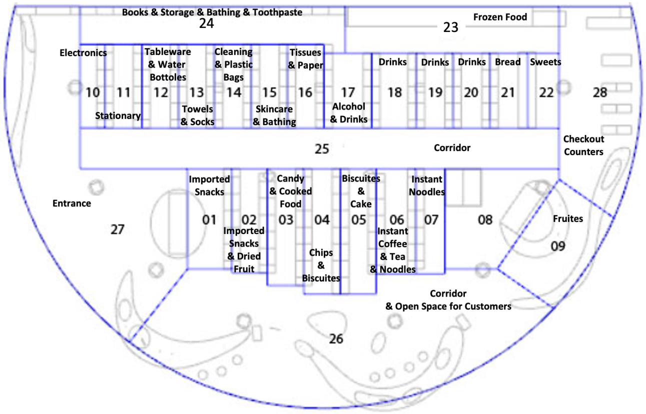

Fig. 6. Layout of supermarket.

Trajectory records are stored in a CSV format each for 394 customers and resampled to 40ms in pre-processing. The following is a sample record: user ID, x, y, and timestamp as 106, -5.14, 3.32, and 2021-01-01T00:00:00.120000…

B. Results

Fig. 7 shows the inclination of customer visitation in the supermarket after noise removal.

Fig. 7. Inclination of customer visitation in supermarket.

Note that most of the users started browsing from an entrance (zone 27), but some from a checkout counter (zone 28). From the figure, the travel distance resonates with the area size of zones in general, meanwhile, the stay time is not necessarily in proportion to the zone size.

9,230 iterations (is equivalent to the number of parameter sets in total) have been attempted in auto-modelling. Fig. 8 shows the mean accuracy of top K performance (*ACC@TopK*) varying on the look-back (*LB*) period.

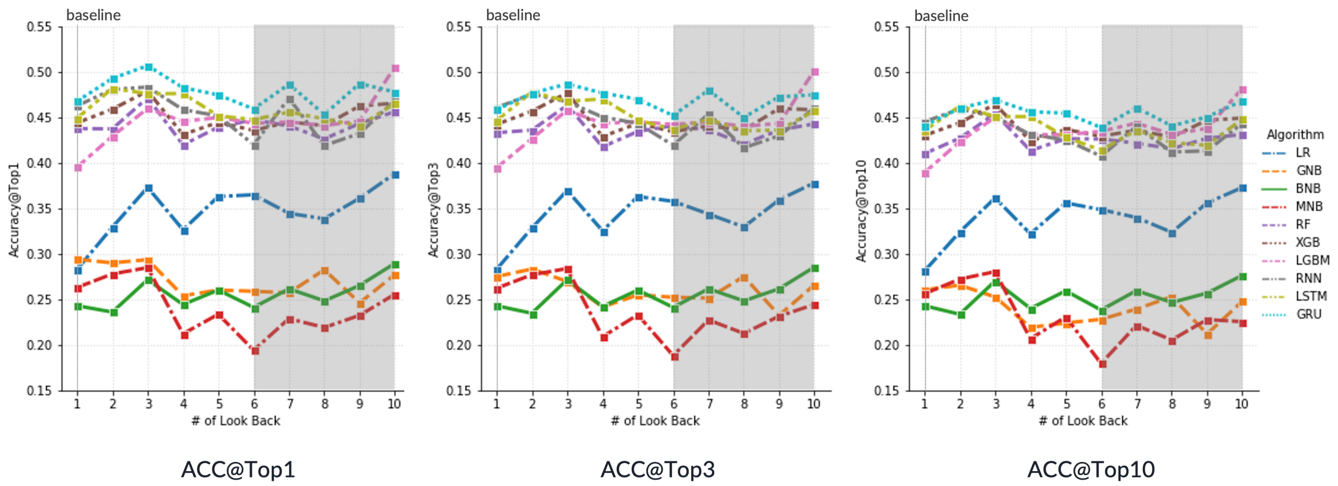

Fig. 8. Accuracy of top K performance.

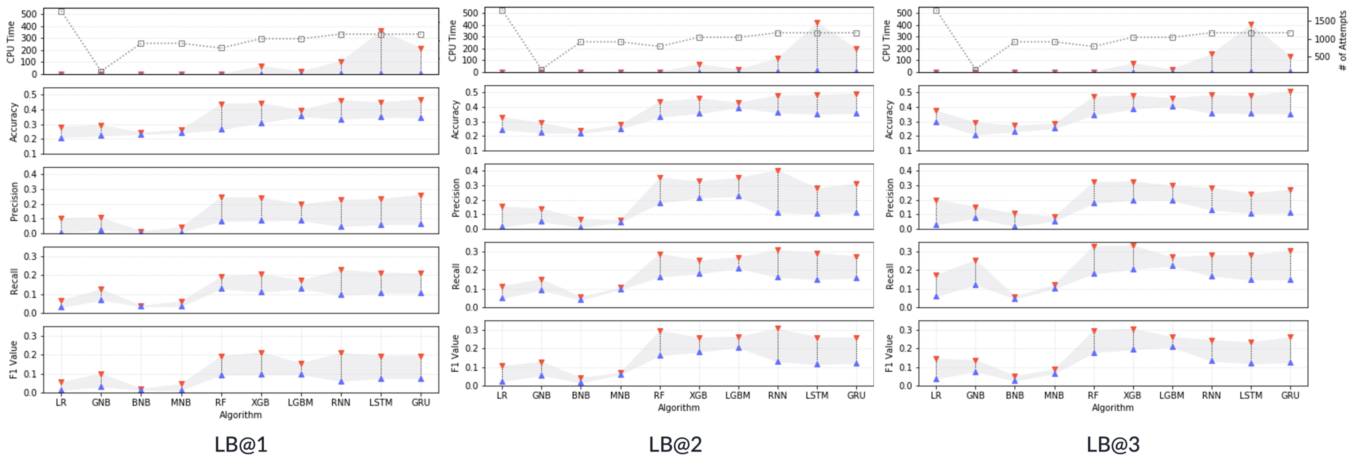

Fig. 9. Metrics varying on *LB@2~3* compared to *LB@1* (baseline).

With *K*=1, 3, and 10, almost all the algorithms commonly have a distinct peak at *LB*=3, and the accuracy is on an uptrend after *LB*=6. Note that there are users who do not have a total length of segments of more than six, and the modelling would have been hence done on such a limited dataset. This study thereby regards the results when *LB*=1~6 as effective results. To recap, GRU showcases the most remarkable performance when *LB*=3 compared to *LB*=1 (baseline).

Fig. 9 depicts various metrics when *LB*=1~3. The performances are generally relative to *LB*. Of all algorithms, neural networks demonstrate better performance though they require large computation cost. On the other hand, tree-based ensemble learning algorithms stand comparison with a performance taking less computing time.

Fig. 10 explains feature impacts when *K*=1 and *LB*=1~3. Clearly, with all features, all the methods achieve the best performance except for the Naïve Bayes approach. It is considered that the Naïve Bayes family suffers from the curse of dimensions when with all features.

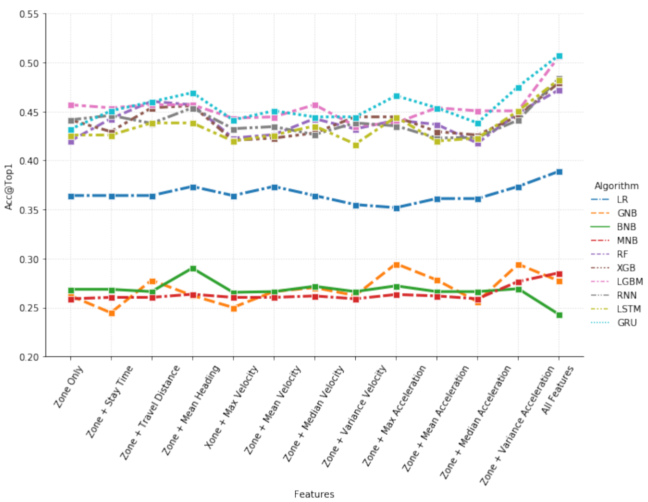

Fig. 10. Feature impacts by various algorithms (*ACC@Top1*, *LB@1~3*).

V. Conclusion and Discussion

The proposed framework has elucidated marked differences among various machine learning algorithms, feature impacts, and metrics given the memory of past contexts. This study catered for insights that customer mobility has been best predicted by backpropagating some nodes information in a supermarket case study and that feature impacts do not necessarily come along with the coherence to all machine learning algorithms.

Yet, the performance of human mobility modelling can get highly affected by layout information, it is hence worthwhile to applicationise an analytical framework just like this study in view of open testing with arbitrary, sparse, and noisy datasets. Last but not least, the prediction would have attained a better performance if the framework took in a lot more trajectory datasets, customised vanilla algorithms, or even utilised point-of-sales information together. These points ought to be placed in future work since this study only had limited access to store details at the time.

For wider applications in the future, this study seeks to apply the framework to different test beds and also integrate with other service platforms such as a map to embody digital twin concepts where both indoor and outdoor mobility scenarios are seamlessly covered.

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References

[1]. A.E. Nuaimi, A.H. Neyadi, N. Mohamed and A.J. Jaroodi, “Applications of big data to smart cities”, Journal of Internet Services and Applications, 6, 25, 2015.

[2]. G. Solmaz et al., “Toward understanding crowd mobility in smart cities through the Internet of things”, IEEE Communications Magazine 57, 4, 40-46, 2019.

[3]. N. Mohammadi and J. E. Taylor, “Urban infrastructure-mobility energy flux”, Energy 140, 1, 716-728, 2017.

[4]. Z. Huang et al., “Modeling real-time human mobility based on mobile phone and transportation data fusion”, Transportation Research Part C: Emerging Technologies 96, 251-269, 2018.

[5]. X. Lu, L. Bengtsson and P. Holme, “Predictability of population displacement”, In Proceedings of the National Academy of Sciences 109, 29, 11576-11581, 2012.

[6]. T. Yabe, K. Tsubouchi, N. Fujiwara et al., “Non-compulsory measures sufficiently reduced human mobility in Tokyo during the COVID-19 epidemic”, Sci Rep 10, 18053, 2020.

[7]. N. Sano, "Estimation of customer behaviour in sales areas in a supermarket using a hidden Markov model", International journal of Knowledge Engineering and Soft Data Paradigms, 5, 2, 135–145, 2016.

[8]. C.J. Petersen, D.B. Pyne, M.R. Portus and B. Dawson, “Validity and reliability of GPS units to monitor cricket-specific movement patterns”, International Journal of Sports Physiology and Performance 4, 3, 381–93, 2009.

[9]. D. Ashbrook and T. Starner, “Using GPS to learn significant locations and predict movement across multiple users”, Personal and Ubiquitous Computing 7, 5, 275–286, 2003.

[10]. F. Calabrese, M. Diao, G. Di Lorenzo, J. Ferreira and C. Ratti, “Understanding individual mobility patterns from urban sensing data: A mobile phone trace example”, Transportation Research Part C: Emerging Technologies 26, 301–313, 2013.

[11]. S. Jiang, Y. Yang, S. Gupta, D. Veneziano, S. Athavale and M. C. González, “The TimeGeo modeling framework for urban motility without travel surveys”, In Proceedings of the National Academy of Sciences 113, 37, E5370–E5378, 2016.

[12]. Y. Pu and P. You, “Indoor positioning system based on BLE location fingerprinting with classification approach”, Applied Mathematical Modelling 62, 654–663, 2018.

[13]. X. Ding, Z. Liu and H. Xu, “The passenger flow status identification based on image and WiFi detection for urban rail transit stations”, Journal of Visual Communication and Image Representation 58, 119–129, 2019.

[14]. M. Alvarez-Campana, G. López, E. Vázquez, V.A. Villagrá and J. Berrocal, “Smart CEI Moncloa: an IoT-based platform for people flow and environmental monitoring on a smart university campus”, Sensors 17, 2856, 2017.

[15]. A. Danalet, B. Farooq and M. Bierlaire, “A Bayesian approach to detect pedestrian destination-sequences from WiFi signatures”, Transportation Research Part C: Emerging Technologies 44, 146–170, 2014.

[16]. C. Chilipirea, M. Baratchi, C. Dobre and M. van Steen, “Identifying stops and moves in WiFi tracking data”, Sensors 18, 11, 4039, 2018.

[17]. P.M. Guadagni and J.D.C. Little, "A logit model of brand choice, calibrated on scanner data", Marketing Science, 2, 3, 203–238, 1983.

[18]. J.U. Farley and L.W. Ring "A stochastic model of supermarket flow", Operations Research, 14, 4, 555–567, 1966.

[19]. P. Wang, H. Wang, H. Zhang, F. Lu and S. Wu, “A hybrid Markov and LSTM model for indoor location prediction”, IEEE Access 7, 185928–185940, 2019.

[20]. P. Wang, Y. Jing and Z. Jianpei, “Indoor trajectory prediction for shopping mall via sequential similarity”, Information 13, 3, 158, 2022.

[21]. T. Anagnostopoulos, C. Anagnostopoulos, S. Hadjiefthymiades, M. Kyriakakos and A. Kalousis, “Predicting the location of mobile users: a machine learning approach”, In Proceedings of the 2009 International Conference on Pervasive Services, 65–72, 2009.

[22]. S. Kim and JG. Lee, “A systematic framework of predicting customer revisit with in-store sensors”, Knowl Inf Syst 62, 1005–1035, 2020.

[23]. M. Chen, Y. Liu, and X. Yu, “NLPMM: A next location predictor with Markov modelling”, Advances in Knowledge Discovery and Data Mining, 8444, 2014.

[24]. M. Chen, Y. Liu, and X. Yu, “Predicting next locations with object clustering and trajectory clustering”, Advances in Knowledge Discovery and Data Mining, 9078, 2015.

[25]. D. Kong and F. Wu, “HST-LSTM: a hierarchical spatial-temporal long-short term memory network for location prediction”, In Proceedings of the 27th International Joint Conference on Artificial Intelligence, 2341–2347, 2018.

[26]. Y. Yoshimura, A. Krebs, and C. Ratti, “Noninvasive Bluetooth monitoring of visitors’ length of stay at the louvre”, IEEE Perv Comput 16(2):26–34, 2017.