Predicting Indoor Location based on a Hybrid Markov-LSTM Model

Peixiao Wang[1](✉), Sheng Wu[1], and Hengcai Zhang[2](✉)

[1] The Academy of Digital China, Fuzhou University, Fuzhou 350002, China
peixiao_wang@163.com

[2] State Key Lab of Resources and Environmental Information System, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
zhanghc@lreis.ac.cn

Abstract. To overcome the problem of dimension curse in the processing of predicting indoor location by using the traditional Markov chains, this paper proposes a novel hybrid Markov-LSTM model to predict the indoor user's next location, which adopt the multi-order Markov chains (k-MCs) to model the long indoor location sequences and use LSTM to reduce dimension through combining multiple first-order MCs. Finally, we conduct comprehensive experiments on the real indoor trajectories to evaluate our proposed model. The results show that the Markov-LSTM model significantly outperforms five existing baseline methods in terms of its predictive performance.

Keywords: Indoor location prediction · Movement trajectory · Markov-LSTM

1 Introduction

As a classical statistical model, the first-order Markov chain (1-MC) has strong interpretability and is widely used in location prediction. However, 1-MC assumes that the location at the next moment is only related to the current location, which significantly limits the predictive performance of the model [1, 2]. To address this deficiency, the multi-order Markov chain (*k*-MC) is proposed [3]. The *k*-MC assumes that the location at the next moment is related to the previous *k* locations but is prone to problems with dimensionality disaster, i.e., its state space explodes with an increase in *k*, which renders *k*-MC less practical in the field of location predictions [4].

Therefore, we propose a hybrid Markov-LSTM model. The model study attempts to combine the advantages of the Markov and LSTM models to improve the performance of the location prediction model. This study makes several significant contributions, which are summarized as follows:

(1) A new multi-step Markov transition probability matrix, which divides the multi-order Markov model into multiple first-order models and solves the shortcomings of the multi-order Markov model in the dimension disaster.
(2) Fusion of the prediction results of the multiple first-order Markov models based on the advantages of the LSTM for predicting long-sequence data. This improved the practicality of the multi-order Markov model for location prediction.

© Springer Nature Switzerland AG 2020
S. Di Martino et al. (Eds.): W2GIS 2020, LNCS 12473, pp. 33–38, 2020.
https://doi.org/10.1007/978-3-030-60952-8_4

2 Methodology

The structure of Markov-LSTM is presented in Fig. 1. Our method is divided into four phases: location sequence detection, multi-step transition probability matrix definition, adjacent locations selection, and fusion multiple Markov chains.

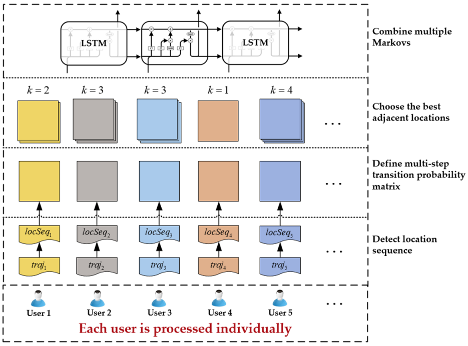

Fig. 1. Markov-LSTM model overall process.

2.1 Definition of the multi-step transition probability matrix

In this study, we used the indoor-STDBSCAN [5] and the nearest-neighbor search to convert the trajectory into a location sequence. In order to improve the practicability of k-MC in location prediction, we propose a novel k-step Markov chain, $\mathrm{MC}^{(k)}$.

Definition 1 (1-Step Transition Probability Matrix). The 1-step transition probability matrix, $\boldsymbol{Y}^{u(1)}$, of user u is equivalent to the 1-order transition probability matrix, $\boldsymbol{Y}_{ij}^{u(1)}$, which represents the probability that user u moves from location l_i through one step to location l_j. $\boldsymbol{Y}_{ij}^{u(1)}$ can be defined with the following expression:

$$\boldsymbol{Y}_{ij}^{u(1)} = \frac{\sum_{p=1}^{m-1}\left|\left\{l_p^u = l_i \cap l_{p+1}^u = l_j\right\}\right|}{\sum_{p=1}^{m}\left|\left\{l_p^u = l_i\right\}\right|} \quad \begin{matrix} \boldsymbol{Y}^{u(1)} \in \mathbb{R}^{N\times N} \\ l_p^u \in locSeq^u \end{matrix} \tag{1}$$

where $locSeq^u$ represents the location sequence, $\left\{l_i^u\right\}_{i=1}^m$, of user u, $\sum_{p=1}^{m-1}\left|\left\{l_p^u = l_i \cap l_{p+1}^u = l_j\right\}\right|$ represents the distance that user u moves from location l_i through one step to location l_j, $\sum_{p=1}^{m}\left|\left\{l_p^u = l_i\right\}\right|$ represents the total distance that user u moves from location l_i through one step to other locations, and Nrepresents the total number of shops in the mall.

Definition 2 (k-Step Transition Probability Matrix). The k-step transition probability matrix, $\boldsymbol{Y}^{u(k)}$, of user u is a $N \times N$ matrix, $\hat{\boldsymbol{y}}^{u(l_i \to *:k)} = \boldsymbol{Y}_{i\to *}^{u(k)}$, which represents the probability that user u moves from location l_i through k steps to other locations. The definitions of $\boldsymbol{Y}^{u(k)}$ and $\hat{\boldsymbol{y}}^{u(l_i \to *:k)}$ for user u can be expressed with Eqs. (2) and (3), respectively:

$$\boldsymbol{Y}^{u(k)} = \mathrm{P}(L^u_{m+1}|L^u_{m-k+1})\ \boldsymbol{Y}^{u(k)} \in \mathbb{R}^{N\times N} \tag{2}$$

$$\hat{\boldsymbol{y}}^{u(l_i\to *:k)} = \mathrm{P}(L^u_{m+1}|L^u_{m-k+1} = l^u_{m-k+1})\ \hat{\boldsymbol{y}}^{u(l_i\to *:k)} \in \mathbb{R}^{1\times N} \tag{3}$$

where $\boldsymbol{Y}^{u(k)}$ can be directly obtained by $\boldsymbol{Y}^{u(1)}$, i.e. $\boldsymbol{Y}^{u(k)} = \left(\boldsymbol{Y}^{u(1)}\right)^k$, L^u_{m-k+1} represents a random variable of user u, $L^u_{m-k+1} = l^u_{m-k+1}$ indicates that user u determines to visit location l^u_{m-k+1} at random variable L^u_{m-k+1} (l^u_{m-k+1} can be obtained in the location sequence $locSeq^u$), $\boldsymbol{Y}^{u(k)}$ describes the effect that cross-location has on the prediction results from another perspective.

2.2 Selection of the best adjacency locations

Similar to the k-MC, the Markov-LSTM model must also determine the hyperparameter, k, i.e., the number of locations that the prediction result depends on. This value is usually determined using cross-validation to minimize the model prediction error [6, 7]. Taking user u with a k value of k_u as an example, when $k_u > 1$, the k-MC can be decomposed based on the following expressions.

$$\begin{cases} \hat{\boldsymbol{y}}^{u(l^u_m\to *:1)} = P\left(L^u_{m+1}|L^u_m = l^u_m\right) \\ \hat{\boldsymbol{y}}^{u(l^u_{m-1}\to *:2)} = P\left(L^u_{m+1}|L^u_{m-1} = l^u_{m-1}\right) \\ \cdot \\ \cdot \\ \cdot \\ \hat{\boldsymbol{y}}^{u\left(l^u_{m-k_u+1}\to *:k_u\right)} = \mathrm{P}\left(L^u_{m+1}|L^u_{m-k_u+1} = l^u_{m-k_u+1}\right) \end{cases} \tag{4}$$

where $\left\{\hat{\boldsymbol{y}}^{u\left(l^u_{m-i+1}\to *:i\right)}\right\}_{i=1}^{k_u}$ represents the prediction results of multiple first-order Markov models for user u.

2.3 Fuse multiple Markov models

For each user, u, we have established k_u first-order Markov models. Therefore, this study combines k_u first-order Markov models to ensure location prediction performance. Considering the order of the k_u first-order Markov model prediction results, i.e. $\left\{\hat{\boldsymbol{y}}^{u\left(l^u_{m-i+1}\to *:i\right)}\right\}_{i=1}^{k}$, we use the LSTM model to fuse k_u results.

3 Experimental results and analysis

3.1 Data sources

The experimental data consisted mainly of Wi-Fi positioning data for 50 users and shop data for a shopping mall in Jinan City, China. The data covered the eight floors of the shopping mall from December 20, 2017, to February 1, 2018. Data for each trajectory included the unique identifier of the user, record upload time, the user's (X, Y) coordinates, and the unique floor identifier. There are 489 shops in the mall. Data for each shop included the shop's unique ID, the shape of the shop (a polygon composed of the coordinate sequence), the shop name, and the floor ID.

3.2 Evaluation metrics and comparative methods

In this study, we treats location prediction as a classification problem. Using $Accuracy@X$, $Precision@X$, $Recall@X$, and $F1-Measure@X$ (top X locations) as quantitative indicators of the evaluation model [8].

To comprehensively evaluate the performance of the Markov-LSTM model, we used five baseline methods for comparison: 1-MC, HMM (Hidden Markov model), RNN (Recurrent neural network), LSTM (Long-short-term-memory network), and GRU (Gated-recurrent-unit network). The prediction performance of HMM, RNN, LSTM, and GRU is related to the number of hidden states. In the comparison experiment, the number of states in HMM was varied among 10, 15, and 20 states. The number of hidden states in RNN, LSTM, and GRU was varied among 64, 128, and 256 states.

3.3 Comparison with baselines

In this section, Fig. 2 compares the prediction performance of the five models.

(1) From an overall perspective. If we take $X = 3$ as an example, the average $Accuracy@3$, $Precision@3$, $Recall@3$, and $F1-Measure@3$ of the 1-MC and HMM were 39.64%, 36.71%, 35.21%, and 35.87%, respectively. The average $Accuracy@3$, $Precision@3$, $Recall@3$, and $F1-Measure@3$ of the RNN, LSTM, and GRU were 64.74%, 62.10%, 55.91%, and 58.84%, respectively. Compared with the Markov-LSTM, the four indicators for the Markov-LSTM improved by 7.33%, 7.47%, 5.46%, and 6.38%, respectively.

(2) From a local perspective, the 1-MC model achieved poor prediction performance, with $Accuracy@3$, $Precision@3$, $Recall@3$, and $F1-Measure@3$ at 28.64%, 24.77%, 26.36%, and 25.54%, respectively. The LSTM model achieved good predictive performance, with $Accuracy@3$, $Precision@3$, $Recall@3$, and $F1-Measure@3$ at 67.79%, 65.78%, 55.15%, and 55.99%, respectively. Overall, the Markov-LSTM model improved indoor location prediction performance significantly by enhancing the $Accuracy@3$ by between 6.29 and 43.43%, $Precision@3$ by between 3.79 and 44.8%, $Recall@3$ by between 9.23 and 35.02%, and the $F1-Measure@3$ by between 13.8 and 39.68%.

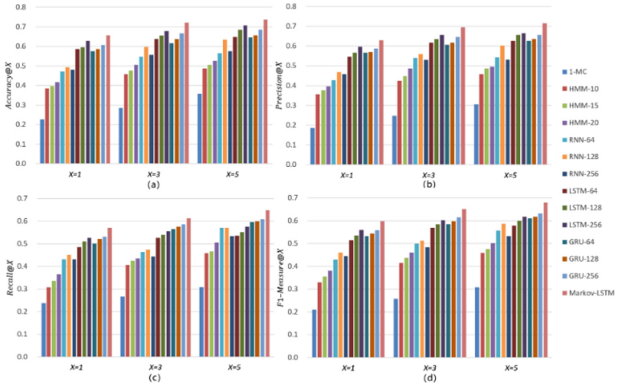

Fig. 2. Comparisons of the baselines using the dataset: (a) location prediction accuracy, (b) location prediction precision, (b) location prediction recall, and (d) location prediction f1-measure.

4 Conclusions

In this study, we proposed a novel hybrid Markov-LSTM model for indoor location prediction. During experiments, we conducted a comparison with five existing baseline methods, including the MC, HMM, RNN, LSTM, and GRU models. Compared with the existing methods, the Markov-LSTM model significantly improved indoor location prediction performance by enhancing the $Accuracy@3$ by between 6.29 and 43.43%, $Precision@3$ by between 3.79 and 44.8%, $Recall@3$ by between 9.23 and 35.02%, and the $F1-Measure@3$ by between 13.8 and 39.68%. This demonstrates the efficiency of the Markov-LSTM model.

Funding. This project was supported by National Key Research and Development Program of China, (Grant Nos. 2016YFB0502104, 2017YFB0503500), and Digital Fujian Program (Grant No. 2016-23).

References

1. Gambs, S., Killijian, M.-O., Nunez del Prado Cortez, M.: Next place prediction using mobility markov chains. In: Proceedings of the 1st Workshop on Measurement, Privacy, and Mobility, MPM 2012, ACM (2012) https://doi.org/10.1145/2181196.2181199
2. Gambs, S., Killijian, M.O., del Prado Cortez, M.N.: Show me how you move and i will tell you who you are. Trans. Data Privacy **4**(2), 103–126 (2011)
3. Sha, W., Zhu, Y., Chen, M., Huang, T.: Statistical learning for anomaly detection in cloud server systems: a multi-order markov chain framework. IEEE Trans. Cloud Comput. **6**(2), 401–413 (2015)
4. Yu, X.G., Liu, Y.H., Da, W., Lei, L.Y.: A hybrid markov model based on EM algorithm. In: International Conference on Control (2006)
5. Peixiao, W., Sheng, W., Hengcai, Z., Feng, L.: Indoor location prediction method for shopping malls based on location sequence similarity. ISPRS Int. J. Geo-Inf. **8**(11), 517 (2019). https://doi.org/10.3390/ijgi8110517

6. Cheng, S., Lu, F., Peng, P., Wu, S.: Short-term traffic forecasting: an adaptive ST-KNN model that considers spatial heterogeneity. Comput. Environ. Urban Syst. pp. S0198971518300140 (2018)
7. Xia, D., Wang, B., Li, H., Li, Y., Zhang, Z.: A distributed spatial–temporal weighted model on MapReduce for short-term traffic flow forecasting. Neurocomputing **179**, 246–263 (2016)
8. Yang, Y.: An evaluation of statistical approaches to text categorization. Inf. Retrieval **1**(1–2), 69–90 (1999)