A Spatially-Adapted SHAP Approach for Interpreting Deep Bike Usage Learning and Prediction

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Abstract

Understanding the spatial dynamics of bike-sharing usage is critical for effective urban planning and mobility resource management. In this study, we propose an interpretable deep learning approach to uncover spatial relationships embedded in bike-sharing activities. Specifically, we develop a spatially-adapted SHapley Additive exPlanations (SHAP)-based method to quantify the spatial dependencies between locations in bike-sharing activities and apply it to interpret the predictions of a bike-sharing model. Extensive experiments upon Citi Bike data from New York City in December 2023 reveal that spatial influence does not strictly follow geographic proximity and is anisotropic. Additionally, non-member users exhibit weaker spatial dependencies in their bike usage behavior, resulting in lower short-term predictability compared to member users. Our studies shed deep insights into the spatial dynamics of bike-sharing systems and provide guidance for more effective service deployment and system design.

CCS Concepts

• Information systems → Geographic information systems; • Computing methodologies → Artificial intelligence

Keywords

Bike-sharing, Deep Learning, Adapted SHAP, Spatial Dependency

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1 Introduction

Bike-sharing has become an integral component of urban transportation systems due to its demonstrated benefits for mobility, public health, and environmental sustainability. With the growing availability of large-scale bike-sharing trip records, many researchers have adopted data-driven deep learning approaches for bike-sharing prediction. Among these efforts, the effectiveness of deep learning models in capturing complex nonlinear interactions within the data has been widely recognized. However, two important gaps remain largely underexplored and warrant further investigation:

- While deep learning models can leverage spatiotemporal data features to enhance prediction accuracy, effective data-driven planning of bike-sharing systems requires an in-depth understanding of the underlying relationships that drive these predictions.
- Bike-sharing activities occur within broader environmental contexts shaped by transportation networks and involve diverse user scenarios. Developing targeted planning strategies demands nuanced insights into these context-specific dynamics.

This study aims to uncover spatial dependency patterns in bike-sharing activities by integrating spatiotemporal deep learning models with explainable artificial intelligence (XAI) techniques. The main contributions of this work are twofold: (1) We have designed a novel spatially-adapted SHapley Additive exPlanations (SHAP) approach to uncover spatial dependencies among locations based on bike-sharing activities. (2) We have conducted extensive data-driven experimental studies across different user types to examine the context-specific predictability and behavioral variability of bike-sharing activities.

2 Related Work

Bike-sharing, as a mode of first-/last-mile travel, is characterized by rapid shifts in the spatial distribution of bikes due to frequent user pick-ups and drop-offs. To capture the temporal dynamics, deep sequence learning models such as long short-term memory (LSTM) networks are commonly employed by formulating bike-sharing as a sequence prediction problem [7]. On the spatial dimension, convolutional neural networks (CNNs) are commonly used for their effectiveness in extracting features from grid-like spatial data [10]. To leverage both spatial and temporal dependencies, hybrid models have been developed for bike-sharing demand forecasting [3]. Convolutional LSTM (ConvLSTM) has been adapted for bike-sharing systems [1]. Lee

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et al. [4] compared several deep learning architectures for bike-sharing demand prediction, demonstrating that ConvLSTM achieved the highest prediction accuracy. However, the intrinsic relationships learned by these models remain largely under-explored. Gaining insights into such relationships is crucial for the informed planning of the city-scale bike-sharing systems, especially when deploying services in areas without historical usage records [11].

SHAP has been widely adopted in XAI due to its solid theoretical foundation and broad applicability. However, most existing applications focus on interpreting non-spatial features. In the context of spatial analysis, Li et al. [5] proposed treating location as an input feature to quantify the effect of spatial locations in machine learning models. In contrast, our study emphasizes the spatial relationship captured by deep learning models, focusing on the relative positioning among features rather than absolute locations. To this end, we develop an adapted spatial SHAP-based method to quantify and visualize the structural spatial dependencies in bike-sharing activities.

3 Data Preparation and Methodology Design

3.1 Data Preparation

We first present our data preparation as follows. The historical bike-sharing activities were obtained from Citi Bike trip records in New York City for December 2023 [2]. Each record includes the timestamp and location of both the pick-up and drop-off, as well as the user type – that is, member or non-member. Previous research suggests that bike stations within 1200 meters exhibit limited variation in their network effect variables and tend to function as substitutes of each other [8]. Accordingly, we partitioned the study area, which covers parts of Manhattan, Brooklyn, and Queens, into an 8 × 8 grid, with each cell covering 1200 m × 1200 m (Figure.1).

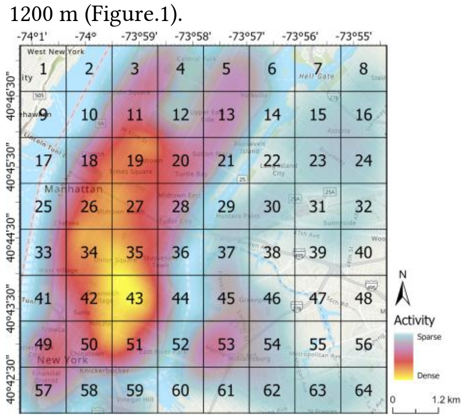


Figure 1: Spatial distribution of bike-sharing activities in December 2023.

Trips with either pick-up or drop-off locations within this area were retained. Records with missing information or with trip durations shorter than 1min or longer than 12hr were excluded. The study period was segmented into 30-min intervals. For each grid cell and time interval, the numbers of bike pick-ups and drop-offs for both user types were calculated and used as input data for the prediction model. We have summarized the total number of bike-sharing activities included in the resulting dataset in Table 1.

Table 1. Total number of bike-sharing activities.

Activity	Member	Non-member	Total
Pick-up	1,352,654	225,841	1,578,495
Drop-off	1,357,493	226,313	1,583,806

3.2 Prediction Model Preparation

The prediction model consists of three ConvLSTM layers, each with 64 units and a kernel size of 3. Each ConvLSTM layer is followed by a batch normalization to stabilize and accelerate training. The model uses a time step of 4, meaning it uses bike-sharing activities from the previous 2 hours to predict for the next half hour. To account for the mutual influence between pick-ups and drop-offs, both types of activities are included in the input features and prediction targets. Specifically, for each grid cell i in time interval t, the bike-sharing activity is represented as $X_{it} = (P_{it}, D_{it})$, where P_{it} and D_{it} denote the number of pick-ups and drop-offs, respectively.

Separate models were trained for members and non-member users. In both cases, data from the first 23 days of the study period were used as training set, while data from the last 7 days were used as the testing set. Table 2 reports the model performance in terms of mean absolute error (MAE), root mean squared error (RMSE), and coefficient of determination (R^2). The MAE and RMSE values indicate that the model achieved satisfactory predictive accuracy for both user types. However, the R^2 values suggest that the model explains non-member's bike-sharing activity less effectively than that of members under the same experimental settings.

Table 2. Performance of prediction model.

User type	MAE	RMSE	R^2
Member	3.13	5.57	0.85
Non-member	1.21	2.36	0.69

3.3 Spatial Dependencies in Bike-sharing

To understand the spatial dependencies embedded in bike-sharing activities that are leveraged by the prediction model, we have adapted SHAP for interpreting our deep learning prediction results. SHAP is grounded in the Shapley value from game theory [9], which attributes each feature's contribution to a model output. The Shapley value for a feature X_i is calculated as:

$$\text{Shapley}(X_i) = \Sigma_{S \subseteq N\{X_i\}} \frac{k!(l-k-1)!}{l!} (f(S \cup \{X_i\}) - f(S)) \quad (1)$$

where N is the full feature set, S is any subset excluding X_i, l is the total number of features, and k is the number of features in S. The function $f(\cdot)$ denotes a certain deep learning model's prediction. The value of Shapley(X_i) reflects the average marginal contribution of X_i across all possible feature combinations.

We note that a key property of Shapley values is additivity, which enables the model output to be decomposed into additive contributions. However, an important challenge of adopting

Shapley lies in the computation, and SHAP is an efficient approach to estimates Shapley values while preserving its additivity [6]. The prediction $\hat{Y}_i$ for observation i can be expressed as:

$$\hat{Y}_i = \text{shap}_0 + \sum_j \text{shap}(X_{ji}) \tag{2}$$

where shap_0 represents the mean model prediction across all observations, and $\text{shap}(X_{ji})$ denotes the SHAP value of a feature j for observation i, representing the contribution of this feature j to the prediction.

In our deep learning prediction setting, the target of our prediction is the bike-sharing activity count X_{it} at location i during a time interval t. In this study, we consider the input features from historical data fall into two groups:

- Temporal features at the same location i : $\{X_{i(t-1)}, X_{i(t-2)}, \cdots, X_{i(t-ts)}\}$ representing historical bike-sharing activities at location i, where ts denotes the number of previous time steps used in the prediction model.
- Spatiotemporal features at other locations $j \neq i$: $\{X_{j(t-1)}, X_{j(t-2)}, \cdots, X_{j(t-ts)}\}$ representing historical bike-sharing activities at other locations j.

Our goal is to quantify the spatial dependencies embedded in bike-sharing activities across locations. We represent the directional influence between locations as:

$$\Phi_{\text{shap}} = \begin{bmatrix} \emptyset_{11} & \emptyset_{12} & \cdots & \emptyset_{1n} \\ \emptyset_{21} & \emptyset_{22} & \cdots & \emptyset_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \emptyset_{m1} & \emptyset_{m2} & \cdots & \emptyset_{mn} \end{bmatrix} \tag{3}$$

where $\emptyset_{ij}$ denotes the contribution of location j to the prediction of bike-sharing activities at location i, calculated by:

$$\emptyset_{ij} = \sum_t \sum_{s=1}^{ts} \text{shap}(X_{j(t-s)})_i \tag{4}$$

where $\text{shap}(X_{j(t-s)})$ is the SHAP value of the bike-sharing activity at location j during time interval $t - s$, and ts is the number of time steps used in the prediction model.

4 Result Demonstration and Discussion

4.1 Strength of Spatial Dependency

Based on Equation (3) and (4), we have quantified the spatial dependencies in bike-sharing activities for both user types. Specifically, Figure 2 illustrates the contributions of historical member pick-ups from all cells toward the predictions of member drop-offs in each of the 64 grid cells, reflecting the spatial dependencies between member pick-up and drop-off locations. Similarly, Figure 3 showcases the contribution of past non-member pick-ups in each of the 64 grid cells to the predicted non-member drop-offs in each cell. The 8×8 grid in the upper left of Figure 2 and 3 corresponds to the grid layout in Figure 1.

We note that, among all the effects demonstrated in Figure 2, the largest-magnitude positive effect is received by Cell 19, centered at the New York Times Square, from its adjacent neighbor Cell 20. This suggests that many member pick-ups in Cell 20 tend to increase the number of drop-offs in Cell 19. In contrast, the largest-magnitude negative effect also targets Cell 19, originating from Cell 35. This implies that members picking up bikes in Cell 35 are more likely to ride to destinations other than Cell 19.

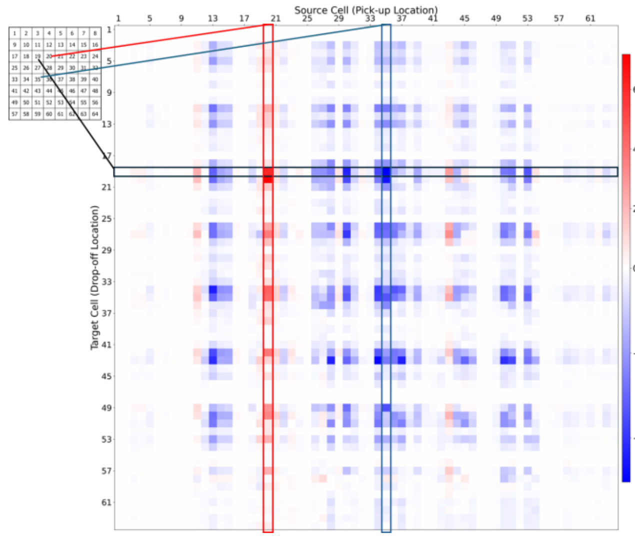


Figure 2: SHAP values of past member pick-ups when predicting member drop-offs in each grid cell.

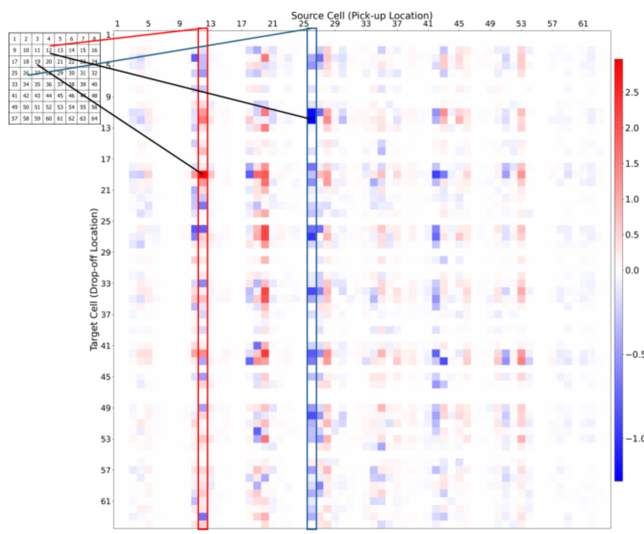
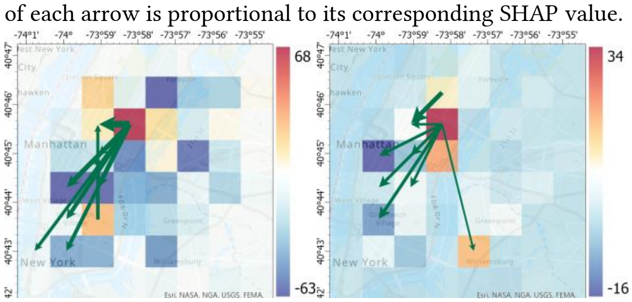


Figure 3: SHAP values of past non-member pick-ups when predicting non-member drop-offs in each grid cell.

The SHAP values for non-member predictions are noticeably lower than those for members, which is consistent with the R^2 value difference reported in Table 2. This suggests that spatial dependencies between pick-up and drop-off locations are generally weaker for non-members than for members, thereby limiting the explanatory power of prediction models that rely solely on historical records. Such a disparity reflects the greater irregularity and unpredictability in the behavior patterns of non-members, which can be addressed through, for instance, inclusion of more granular user studies by the service operators.

By summing up the SHAP values across each column in Figure 2 and Figure 3, Figures 4(a) and 4(b) present the aggregate influence that each grid cell exerts on others when predicting bike drop-offs based on prior pick-ups for the two user types. A higher positive value in Figure 4 indicates that a grid cell is more likely to serve as a trip origin and contributes to bike drop-offs in other locations. Conversely, a strong negative value indicates that pick-ups in the corresponding cell tend to stay localized, potentially reducing bike availability in other areas and thus negatively impacting the number of drop-offs elsewhere. The green arrows in Figures 4(a) and 4(b) represent the top 10 largest positive SHAP values extracted from Figures 2 and 3, respectively, with each arrow pointing from the source cell to the target cell. The width of each arrow is proportional to its corresponding SHAP value.



(a) Member (b) Non-member

Figure 4: Summed SHAP value with (a) member riders and (b) non-member riders of each grid cell when predicting bike drop-offs based on past pick-ups.

4.2 Structure of Spatial Dependency

From a structural perspective, our experimental results reveal three key patterns as summarized below.

First, the spatial dependencies in bike-sharing activities do not strictly adhere to spatial proximity. For instance, in Figure 2, the SHAP values in the row for target grid cell 35 indicate that it receives a greater contribution from cell 20 than from its adjacent cell 43, even though both cell 20 and cell 43 have strong outward influence as shown in Figure 4(a).

Second, the spatial dependencies in bike-sharing activities are anisotropic, meaning that the direction and strength of influences from a location can vary across surrounding areas. As illustrated in Figure 4 (a) and (b), the grid cells with the strongest outward spatial influence do not exert uniform effects in all directions. This directional variation may be attributed to physical or infrastructural barriers. In fact, as shown in Figure 1, the study area is divided by a river, which may limit the bike ridership interactions between the two sides. As a result, the most pronounced spatial dependencies are concentrated among grid cells on the left side of the river.

Third, we note that spatial dependencies in bike-sharing exhibit structural differences between user types. As illustrated in Figure 4, the strongest spatial dependency for non-members originates from grid cell 12 near the New York Central Park, while for members, two of the top ten positive spatial dependencies originate from grid cell 43 in East Village and target cell 19 centered in Times Square.

5 Conclusion and Future Work

We propose an adapted SHAP-based method to quantify the spatial relationships captured by deep learning models in predicting bike-sharing activities. Experimental results reveal that spatial dependencies in bike-sharing are anisotropic, do not necessarily align with geographic proximity, and vary significantly across user types. The findings underscore the need for context-specific approaches in bike-sharing planning. The proposed method is also applicable to analyzing other types of mobility flows, such as ride-hailing services, with the potential to inform transportation planning and support the advancement of sustainable mobility systems.

As a preliminary study, this paper focuses on uncovering and quantifying spatial dependencies based on a fixed-size grid using a deep learning model. Future research will build on this foundation and interpret temporal dependencies, and conduct comparative analyses of spatial dependencies across different scales to yield finer-grained insights.

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