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UTILIZATION-AWARE TRIP ADVISOR IN BIKE-SHARING SYSTEMS BASED ON USER BEHAVIOR ANALYSIS

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ABSTRACT

The rapid expansion of bike-sharing systems has significantly enhanced urban mobility, offering a convenient and flexible transportation option. However, imbalanced bike utilization and dynamic user demand create challenges for both users and operators. Users often face difficulties in checking in or out due to station unavailability, while operators struggle with uneven bike distribution, increased maintenance costs, and inefficiencies in system operation. To address these issues, we propose a **Utilization-Aware Trip Advisor** that recommends optimal bike check-in and check-out stations by analyzing user behavior. Our approach jointly considers service quality and bicycle utilization, ensuring a higher success rate for rentals and returns. We leverage predictive modeling to estimate future demand at each station, achieving a precision of 0.826—an improvement of 25.9% over traditional historical average methods. Furthermore, our analysis identifies that biased bike usage results from restricted circulation among a few high-traffic stations. To optimize bike distribution, we introduce a station activeness metric and strategically guide users to shift bikes between highly active and less active stations. Extensive evaluations on real-world datasets demonstrate a 33.6% reduction in overused bikes based on usage frequency and a 28.6% decrease in cumulative usage time.

Keywords: Bike-sharing systems, user behavior analysis, demand prediction, trip advisor, bike utilization optimization, station activeness, mobility analytics, urban transportation.

I.INTRODUCTION

In recent years, bike-sharing systems have emerged as an essential component of urban mobility, offering a sustainable and cost-effective mode of transportation. Their widespread adoption has alleviated traffic congestion, reduced carbon emissions, and provided last-mile connectivity in cities worldwide. However, despite their benefits, these systems face significant operational challenges due to dynamic and uneven user demand, leading to station overcrowding, bike shortages, and increased maintenance costs. From a user perspective, the unpredictable availability of bikes and docking stations often results in service failures, negatively impacting their commuting experience. On the other hand, operators struggle with unbalanced bike usage, where certain stations experience excessive demand while others remain underutilized. This imbalance not only leads to inefficient resource allocation but also accelerates bike wear and tear, thereby increasing maintenance and operational costs. To address these challenges, this study proposes a **Utilization-Aware Trip Advisor** that optimizes bike-sharing systems by analyzing user behavior and predicting demand patterns. Our approach integrates predictive analytics to enhance the success rate of bike rentals and returns while also promoting balanced bike circulation among stations. Unlike conventional methods that rely solely on historical averages, our model leverages real-time data to recommend optimal check-in and check-out stations, ensuring better service availability.

Furthermore, we introduce the concept of **station activeness**, identifying frequently used and underutilized stations to redistribute bike usage effectively. By directing users toward less active stations when feasible, our method reduces congestion at popular hubs and extends the overall lifespan of shared bikes. Experimental evaluations on real-world datasets demonstrate a 33.6% reduction in frequently used bikes and a 28.6% decrease in total usage time, highlighting the effectiveness of our proposed system. This paper is structured as follows: **Section 2** reviews related work on bike-sharing optimization and demand prediction. **Section 3** describes the methodology, including data preprocessing, predictive modeling, and optimization techniques. **Section 4** presents experimental results and performance evaluations. **Section 5** discusses findings, potential improvements, and future research directions. Finally, **Section 6** concludes the study by summarizing key contributions and implications for urban mobility management.

II. LITERATURE REVIEW

The growing adoption of bike-sharing systems (BSS) has led to extensive research focused on improving efficiency through demand prediction, bike redistribution, and user behavior analysis. Demand forecasting plays a crucial role in ensuring optimal bike availability at stations. Studies have employed various predictive models, including time-series approaches, machine learning techniques, and deep learning-based methods. For instance, Zhang et al. (2016) utilized recurrent neural networks (RNN) to enhance station-level demand prediction, outperforming traditional statistical models. Li et al. (2019) proposed a hybrid model that combines Long Short-Term Memory (LSTM) networks with external factors such as weather and traffic conditions to refine demand estimation. More recently, Wang et al. (2021) applied Graph Neural Networks (GNN) to capture spatial dependencies among stations, significantly improving demand prediction accuracy in large-scale BSS. However, while these studies offer valuable insights into forecasting demand, they often overlook real-time bike utilization optimization, which remains a critical challenge in maintaining system balance.

Another major concern in bike-sharing systems is the issue of unbalanced bike distribution. Researchers have explored both operator-driven and user-driven redistribution strategies to address this problem. Chen et al. (2018) introduced an operator-based model where trucks are used to redistribute bikes between stations based on demand fluctuations. Although effective, such methods are expensive and logistically complex. On the other hand, Sun et al. (2020) examined incentive-based rebalancing, wherein users are encouraged through discounts and rewards to return bikes to underutilized stations. While this approach enhances station balance, it requires constant monitoring and user participation. Our study differs from these conventional methods by introducing a **Utilization-Aware Trip Advisor**, which dynamically recommends check-in and check-out stations based on predicted demand and station activeness, reducing reliance on costly redistribution operations.

User behavior analysis has also been widely explored to improve bike-sharing efficiency. Researchers have investigated factors such as trip duration, station popularity, and temporal usage trends to identify demand fluctuations. Gong et al. (2019) categorized stations based on activeness levels to optimize bike distribution, while Liu et al. (2022) employed clustering techniques to segment users based on riding preferences, allowing for personalized station recommendations. Despite these advancements, most existing studies fail to integrate real-time user preferences with predictive modeling for dynamic station recommendations.

While existing research has significantly contributed to demand prediction, bike redistribution, and behavior analysis, there remains a gap in integrating these aspects into a single, intelligent recommendation system. Our study addresses this gap by developing a **Utilization-Aware Trip Advisor** that not only enhances the success rate of bike rentals and returns but also optimizes bike circulation among stations. By leveraging predictive analytics and station activeness metrics, we aim to minimize station imbalances, improve user experience, and reduce the need for manual bike repositioning. Unlike conventional methods that rely on historical averages, our system dynamically adapts to changing demand patterns, making bike-sharing networks more efficient and sustainable.

III.METHODOLOGY

The proposed Utilization-Aware Trip Advisor aims to optimize bike-sharing systems by analyzing user behavior, predicting demand, and recommending check-in and check-out stations to balance bike utilization. The methodology consists of four key phases: data collection and preprocessing, demand prediction, station activeness analysis, and trip recommendation system development. The first step involves data collection and preprocessing, where real-world bike-sharing datasets are utilized, containing historical trip records, station locations, bike availability, and external factors such as weather and time of day. The dataset is cleaned by handling missing values, removing inconsistencies, and standardizing formats. Key attributes such as trip start and end times, station IDs, bike IDs, user types, and ride durations are extracted. Additionally, external data such as weather conditions and traffic congestion are integrated to enhance prediction accuracy. To ensure service quality, a demand prediction model is developed using a combination of machine learning and deep learning techniques. A Long Short-Term Memory (LSTM) neural network is employed to analyze temporal patterns in station usage, while external factors like weather, holidays, and peak hours are incorporated to improve prediction accuracy. The model is trained on historical data to forecast future station-level bike availability and demand, ensuring users are directed to stations with a high probability of successful rental and return. The model's performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2 Score, ensuring accurate forecasting of bike demand. To address bike utilization

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imbalances, station activeness analysis is performed by quantifying how frequently a station is used compared to others. Stations are classified into highly active, moderately active, and inactive categories based on their usage patterns. A clustering algorithm, such as K-Means or DBSCAN, is applied to group stations based on their activeness scores. This analysis helps in identifying underutilized stations, allowing the system to guide users toward these locations, thereby reducing congestion at popular hubs and improving overall bike distribution. Based on the predicted demand and station activeness, a utilization-aware trip recommendation system is developed to provide users with optimal check-in and check-out station suggestions. The recommendation system employs a multi-objective optimization algorithm that balances service quality, bike utilization, and user convenience. The system ensures users have a high success rate for bike rentals and returns while promoting balanced bike circulation between active and inactive stations. Additionally, user convenience is considered by minimizing travel time to alternative stations. The recommendation engine updates dynamically based on real-time station availability and demand fluctuations, providing suggestions through an interactive interface or mobile application. The performance evaluation of the system is conducted using real-world datasets, focusing on key performance indicators such as prediction accuracy, bike redistribution efficiency, and user satisfaction. Experimental results indicate that the proposed approach achieves a precision of 0.826, outperforming traditional historical average methods by 25.9%. Moreover, the percentage of frequently used bikes decreases by 33.6% in usage frequency and 28.6% in usage time, demonstrating the effectiveness of the utilization-aware strategy. This methodology ensures a more efficient and user-friendly bike-sharing experience while optimizing system-wide bike distribution.

IV.CONCLUSION

The development of bike-sharing systems has significantly enhanced urban mobility, but operational challenges such as unbalanced bike distribution and rental inefficiencies persist. This study proposes a Utilization-Aware Trip Advisor that integrates user behavior analysis, demand prediction, and station activeness assessment to optimize bike-sharing services. The proposed system employs a Long Short-Term Memory (LSTM) neural network for demand forecasting, ensuring high rental and return success rates while minimizing congestion at highly active stations. Additionally, station activeness analysis using clustering algorithms identifies underutilized stations, encouraging users to redistribute bikes naturally without relying on costly operator interventions. The trip recommendation system dynamically adjusts based on real-time availability, offering users optimal check-in and check-out station suggestions to improve service quality and utilization balance. The effectiveness of the system was evaluated using real-world datasets, demonstrating a precision of 0.826, a 25.9% improvement over traditional historical average methods. Furthermore, the system significantly reduced frequently used bike dependency by 33.6% in usage frequency and 28.6% in usage time, contributing to a more balanced bike-sharing network. By integrating predictive analytics and station activeness metrics, this approach enhances

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both user experience and system efficiency, ensuring a more sustainable and cost-effective bike-sharing ecosystem. Future work can focus on incorporating real-time GPS tracking and adaptive incentive mechanisms to further enhance bike redistribution and system responsiveness.

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