“Bike Sharing”+”Deep Learning”

A bike sharing system provides convenient and sustainable urban mobility to users, while governments solve problems such as traffic congestion, environment, resident health, etc. The sharing system is generally conducted through dock-based and dockless services which are distinguished from restriction of the rent or return locations. The dock-based services require dock planning with comprehensive PoI analyses of the cities and existing transportations (e.g., bus, subway, bicycle path, etc.). The dockless services provides better flexibility to user mobility, however, it requires operators to take expensive cost due to sidewalk blocking or bicycle theft and damage controls. Hence, inadequate service operations lead to oversupply or service failure, as in China's bicycle grave case [2]. Furthermore, imbalance of the bike supply-demand is inevitable problem of these services due to spatial characteristics of the cities. The current rebalancing solution is collecting and reallocating bikes by other vehicles, despite of their time intensive and high-cost operations.

Early studies on bike sharing systems are mostly done to correlate the bike service demands with factors such as weather, built environment, public transportation, station level, socio-demographic effects, temporal factors, and safety [3, 4]. Most of related studies utilize deep learning based on bike rental data to optimize the rebalancing problem in the sharing systems. The DL-based methods approach the problem using Reinforcement learning that calculates reward of the action (i.e., decision) for optimal strategy or Supervised learning that predicts bike demand, supply, or their gap based on historical data. To this end, Convolutional Neural Networks to learn spatial characteristics of the region data and Recurrent Neural Network families to utilize the temporal characteristics of mobility are used [5]. These works evolve into using demand and supply prediction model that utilize Graph Neural Networks to effectively learn correlation between rental and return points [6]. Furthermore, an influencing factor-based clustering technique is used together to improve prediction accuracy [7]. In recent studies, the prediction models improve accuracy performance using fusion layers and residual connections on multiple input data such as geographical or meteorological information, and recent mobility patterns [5][8]. Despite these efforts, these studies present only prediction results or performances, while rebalancing problem remains as challenge task.

The datasets for model training and testing contains only bike rental and return location of the user trips. This is rational by practical difficulties in collecting and analyses on huge amount of urban data. However, GPS tracking data of the user trips can improve the user's service experience. The user trip data using shared bikes in various regions such as New York, Citybike in Washington DC, Chicago, Singapore, and Taipei are publicly opened without detailed route information (i.e., GPS coordinates). The GPS information enables real-time inference applications to provide location-based services, since the data can specify the current location of the bikes (or users). For example, a user's real-time movement pattern can track bike conditions or user emergencies, and can approximate optimal rebalancing strategy that includes location, quantity, and time of relocation by predicting bike flows in real-time. Moreover, the accumulated data can be used for DL/ML-based analyses on low interest areas in the city, urban reconstruction, and commercial district developments.

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