“Bike Sharing”+”Deep Learning”

A bike sharing system provides convenient and sustainable urban mobility to users, while government solves problems such as traffic congestion, environment, resident health, etc. General types of bike sharing system are dock-based and dockless systems, where dock refers rental and return area for users. Dock-based system requires dock installation with comprehensive analyses on Point of Interest (PoI) and existing transportation systems (e.g., bus, subway, bicycle path, etc.) of target city. Dockless system provides better flexibility for user mobility, however, it takes expensive cost due to sidewalk blocking or bicycle theft and damage controls. Imbalance problem of bike supply-demand is inevitable for both system types since user mobility trend follows topographical characteristics or spatial interest of target city. Furthermore, inadequate solution of this problem leads to bike oversupply or system failure as shown in China's bike grave [2]. Hence, the current solution rebalances bikes deployment through collecting and reallocating with other vehicles, despite of its time intensive and high-cost operations.

Early studies on bike sharing system correlate user 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 bike rental data based Deep Learning (DL) to optimize the imbalance problem of target city. A supervised DL models predicts user demand, bike supply, or their gap using historical bike sharing data.

The prediction models use convolutional neural networks to learn spatial characteristics of target region data and recurrent neural network families to utilize temporal characteristics of mobility [5]. These works evolve to the models using graph neural networks which extract and learn correlation of rental and return points [6]. Furthermore, influential factor-based clustering technique improves 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 mobility patterns [5][8]. However, these studies present only prediction results or performances in terms of DL models, while rebalancing problem remains as challenge task.

Datasets for model training and testing contains only bike rental and return location of the user trips, due to difficulties of collecting or analyzing huge amount of urban data. However, GPS tracking data of the user trips can improve user's experience of sharing bike. The bike sharing datasets in various regions such as New York, Washington DC, Chicago, Singapore, and Taipei are available online although detailed route information (i.e., GPS coordinates) are not included in the datasets. The GPS information enables real-time inference application to provide location-based services, since the data can specify the current locations of bikes (or users). For example, real-time movement pattern can track bike conditions or user emergencies, and can approximate optimal rebalancing strategy that includes location, quantity, or time by predicting bike flows. Moreover, accumulated GPS data with DL analysis can specify lower interest area of target city for urban reconstruction, and commercial district developments.

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