Predicting bicycle demand by incorporating station-specific spatial features in a graph convolution networks model

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Abstract

The primary aim of this study is to predict daily bicycle rental volumes at each station, addressing supply-demand imbalances. Previous research has primarily focused on predicting rental volumes using weather data and historical patterns. Recent studies have shown improvements by incorporating graph data to model station relationships. However, the comprehensive characterization of node properties through graph data has been overlooked. Therefore, a new Graph Convolution Network is introduced, depicting spatial station traits. Each Seoul station is considered a node, revealing inter-station connections through rental records. Matrices are employed to define spatial traits and past rental patterns. The output, streamlined into a one-dimensional form, integrates weather variables into a Fully Connected Network (FCN) for efficient daily bicycle demand prediction, outperforming other models.

Introduction

These days, there is a growing demand for personal transportation, driven by a preference for eco-friendly and healthy lifestyles [1], as well as the rapid spread of COVID-19. According to Qiumeng Li's research [2], shared bicycles are recognized as an environmentally friendly mode of transportation, reducing carbon emissions by 108-120g per kilometer. Additionally, due to the swift spread of COVID-19, the government implemented gradual social distancing policies, leading to a decrease in public transportation usage. Comparing the Seoul public transportation usage before and after COVID-19 in 2020, the metropolitan and urban railway usage decreased by 25.0 percent, and city bus usage decreased by 27.4 percent [3].

However, the major challenge for the efficient operation of a bicycle-sharing system is the imbalance between supply and demand [4]. To address this and enhance user satisfaction, accurately predicting bicycle demand at docking stations is essential [5].

Previous studies have employed various methods to predict bicycle demand. Chen et al. [6] modeled the relationships between bicycle stations using Dynamic cluster-based prediction, while Zhang et al. [7] used LSTM to learn time dependencies, considering real-time passenger information in public transportation. Subramanian et al. [8] predicted bicycle demand using various time-series and machine learning algorithms such as LSTM, GRU, RF, ARIMA, and SARIMA, comparing their performances.

In this paper, we developed a Graph Convolutional Network pro (GCN-pro) model to predict demand at each rental station, utilizing historical rental data, spatial data, and weather data. Frade and Ribeiro [9] predicted demand using different weather features like temperature and precipitation, extracting patterns in weekday and monthly total demand as temporal characteristics. Thomas et al. [10] considered the association of bicycle riding locations with destinations and added location data to the analysis along with weather data. It was confirmed that weather and location data play a crucial role in predicting bicycle demand. Based on this, we conducted the project by incorporating location and weather data.

Previously, Kim et al. [11] utilized a GCN model for bicycle demand prediction. Their model treated bicycle docking stations as nodes, with connections between nodes represented by an adjacency matrix. In contrast to Kim et al.'s model, our paper added spatial features to the nodes (stations). While the previous study analyzed using the connectivity of each station and weather data, our paper aimed to contribute to more effective demand prediction by adding nearby 500m spatial data. The nearby 500m spatial data includes the number of subway stations, bus stops, and bicycle roads by type.

Utilizing the background knowledge and technological advancements mentioned above, this study endeavors to predict demand at each bicycle rental station more accurately. The research includes the creation of a specially curated dataset and the reconstruction of the model architecture. By utilizing the GCN-pro model to predict daily rental counts, we anticipate contributing to the more systematic management of the "Ddareungi" system.

Data Collection and Preprocessing

Bicycle rental history data

The daily usage information data for Seoul's public bike rental stations was downloaded from 'Seoul Open Data Plaza.' Rental information for each station is contained in this dataset, and preprocessing was performed to group this information by rental station, calculating the daily rental counts for each station.

Spatial data

Spatial data was employed to extract information about facilities within a 500-meter radius [12] of Seoul bicycle stations. Data downloaded from 'Seoul Open Data Plaza' and 'Smart Seoul Map' included information about bus stops, subway stations, schools, universities, apartments, cultural facilities, and large academies [11]. Spatial data preprocessing was performed to determine the count of these facilities around each bicycle station. Buildings that closed or were demolished before 2022 and those that were constructed or opened after 2022 were excluded.

Regarding the processing of bicycle roads in the spatial data, roads with a radius of 500 meters centered around bicycle stations were formed by connecting bending points. Two scenarios were considered: in the first scenario, roads were counted if at least one bending point was within a 500-meter radius to prevent duplicates. In the second scenario, when all bending points were outside the 500-meter radius, linear equations and the distance from the bicycle station to the intersection point were used to count roads that were less than 500 meters. These classified road variables were divided into A and B types, separate and unseparated, and categorized according to road characteristics as shared roads, dedicated roads, priority roads, and car-only lanes, considering the significance of bicycle priority roads [13].

Through this preprocessing, spatial data consisting of 15 variables within a 500-meter radius for each bicycle rental station was generated.

weather data

Seoul's ASOS data was obtained from the 'Korea Meteorological Administration' to acquire nine weather variables for demand prediction. While the precipitation variable had numerous missing values, we handled them by replacing NA with 0, considering it as the absence of rain.

This preprocessing resulted in a time-series format containing nine weather variables spanning from January 1, 2022, to December 31, 2022.

Methodology

Framework: GCN - pro

The general framework of the Graph Convolutional Network (GCN) model typically comprises nodes and edges, representing relationships between nodes. [14] In this study, bicycle stations are designated as nodes, and the relationships between stations are defined as edges. [15] Specifically, the relationships between stations are characterized as the connectivity between bicycle rental and return stations, utilizing historical data on rentals and returns. [11] The GCN model proposed in this paper integrates a novel spatial feature—specific to individual stations—that has not been addressed in previous literature. Contextual spatial data, including proximity to subway stations, bus stops, and residential areas, is incorporated. The variables within these spatial features, influencing actual rental demand, are selected using the Kruskal-Wallis test. Only these significant features are then incorporated into the model, enhancing its performance. The nomenclature used to denote this model is 'GCN-pro.'

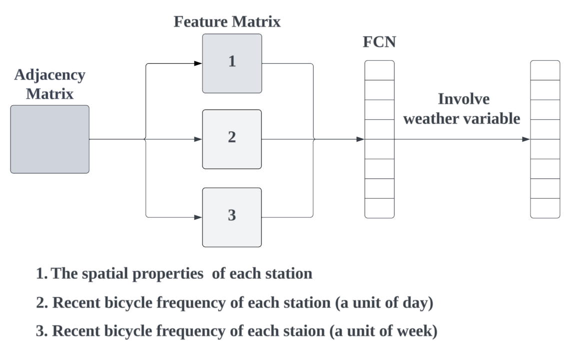

Fig 1. Schema of the GCN-pro

The matrices, which represent the spatial information of nearby subway stations, bus stops, and residential facilities, as well as the matrices containing data for bicycle rentals in the preceding days and weeks, were separately constructed. Each matrix was autonomously processed by the GCN model to learn its distinct features. To construct a unified model integrating all these features, the outputs from each model were elongated into one-dimensional shapes and concatenated. Consequently, the model was designed to learn the spatial characteristics of stations and historical bicycle usage patterns. Weather variables for the prediction date, such as 'precipitation' and 'temperature', were allocated. These components were integrated into a Fully Connected Network (FCN) model, resulting in the calculation of the anticipated demand for each station on the predicted date.

Graph convolution network

The utilization of the Graph Convolution Network (GCN) model serves as a fundamental tool in addressing complex traffic issues [16]. The decision to adopt GCN is rooted in its distinct capability to capture and analyze the intricate relationships between stations present in bicycle rental systems. Previous studies have also recognized the potential of this model and sought to predict bicycle demand using the GCN model.

Adjacency Matrix: Interaction among stations

The interactions between bicycle stations are represented using the total historical records of bicycle rentals and returns. The adjacency matrix is structured so that rows and columns correspond to station numbers with identical station numbers. Rows represent the rental station numbers, while columns depict the return station numbers. The adjacency matrix is constructed by summing the occurrences of rental and return station number pairs across all historical rental and return records.

$$A_{ij} = \sum RR_{ij}$$

A_{ij} denotes the adjacency matrix containing information on rentals from station i and returns to station j, while $\sum RR_{ij}$ signifies the total count of bicycles moved from station i to station j.

$$A_{ij}^{\text{scaled}} = \frac{(A_{ij} - \text{Min})}{\text{Max} - \text{Min}}$$

Here, A_{ij}^{scaled} denotes the scaled matrix, where Max and Min represent the maximum and minimum values within matrix A_{ij}. The scaled matrix, denoted as $\tilde{A}$ (derived from A_{ij}^{scaled}), is further utilized to form the normalized symmetric Laplacian matrix.

$$L^{\text{sym}} = \tilde{D}^{(-1/2)} \tilde{A} \tilde{D}^{(-1/2)}$$

$\tilde{D}$ is the diagonal matrix derived from the matrix $\tilde{A}$, and L^{sym} is the normalized symmetric Laplacian Matrix obtained by multiplying both sides of the scaled adjacency matrix with the power of -1/2 of the diagonal matrix. The construction of a symmetric Laplacian Matrix serves the purpose of efficient information management when performing operations with the feature matrix in eigenvalue-eigenvector forms [17].

Feature Matrix 1: spatial feature by station level

Spatial feature by station level

This research introduces a novel approach to constructing spatial matrices that have not been explored previously. It includes the spatial characteristics specific to individual bicycle stations, encapsulating parameters such as the number of transportation facilities, residential households, and other related features within a 500-meter vicinity of each station. The rows of the matrix correspond to a total unique bicycle stations, while the columns represent 15 distinct spatial characteristics.

$$F_{\text{spatial}}^{\text{scaled}} = \frac{F_{\text{spatial}} - \text{Min}}{\text{Max} - \text{Min}}$$

The spatial matrix F_{spatial} is transformed into values between 0 and 1 using min-max scaling, aiming to prevent the model from biased computations towards specific features.

Examining the Impact of Spatial Features on Bicycle Rental Quantities

A comprehensive investigation was conducted to examine whether a total of 15 spatial features exert an influence on actual rental quantities. In the initial phase of the study, groups were formed based on quartiles according to the number of spatial features, resulting in four distinct categories. The null hypothesis posited that "there is no difference in rental quantities among groups with different numbers of spatial features." To test this null hypothesis, the Kruskal-Wallis test, a non-parametric method, was employed. Typically used when the assumption of homogeneity of variance is not met among groups under examination, the Kruskal-Wallis test verifies the presence of differences in means among three or more groups. Given that the groups in this study did not satisfy the assumption of homoscedasticity, the Kruskal-Wallis test was chosen. The significance level was set at a p-value of 0.05. Upon establishing the statistical significance through this test, the modeling was constructed by incorporating only the spatial features deemed meaningful. These spatial features encompass various factors, including the 'number of nearby bus stops,' 'number of nearby subway stations,' 'number of nearby schools,' and various bicycle paths, totaling 11 features.

Table 1. Results table for Kruskal-Wallis test

Spatial feature	**P-value**
$Busstation$	7.72e-18
$Trainstation$	7.74e-15
$School$	0.01
$Apartmenthousehold$	0.04
$Culturalfacility$	0.30
$University$	0.83
$Academey$	0.18
$(A)Mixed-UseRoad(Non-Separated)$	4.66e-08
$(A)ExclusiveBicycleLane$	1.86e-24
$(A)SeparatedMixed-UseRoad$	0.0003
$(A)ExclusiveBicycleLaneforVehicles$	6.15e-05
$(B)ExclusiveBicycleLane$	1.55e-05
$(B)SeparatedMixed-UseRoad$	0.001
$(B)Mixed-UseRoad(Non-Separated)$	0.46
$(A)BicyclePriorityRoad$	7.29e-10

Feature Matrix 2: Historical Bicycle Rental Records

One of the most crucial attributes in predicting bicycle demand is the incorporation of historical rental records. Bicycle rental history amalgamates daily rental records from a few days preceding the prediction date and weekly rental records from several preceding weeks. Rows represent distinct station numbers, while columns encapsulate information regarding past rental quantities. 't' is assumed as the forecast date for demand, and the matrix illustrates the rental history preceding 't'. For the daily historical rental matrix, it showcases the rental volumes for several days before 't'. Regarding the weekly historical rental matrix, it presents the rental volumes over several weeks from 't'.

GCN propagation

In this chapter, the process of propagation will be discussed, delving into how the matrices created earlier are used for training within the model.

$$H_1^{(0)} = F_{\text{spatial}}^{\text{scaled}}$$

$$H_2^{(0)} = F_{\text{day}}$$

$$H_3^{(0)} = F_{\text{week}}$$

$F_{\text{spatial}}^{\text{scaled}}$ is designated as the first layer of matrix H_1, F_{day} as the first layer of matrix H_2, and F_{week} as the first layer of matrix H_3.

$$H_1^{(l+1)} = \sigma(\hat{D}^{(-1/2)}\hat{A}\hat{D}^{(-1/2)}H_1^{(l)}W^{(l)})$$
$$H_2^{(l+1)} = \sigma(\hat{D}^{(-1/2)}\hat{A}\hat{D}^{(-1/2)}H_2^{(l)}W^{(l)})$$
$$H_3^{(l+1)} = \sigma(\hat{D}^{(-1/2)}\hat{A}\hat{D}^{(-1/2)}H_3^{(l)}W^{(l)})$$

Where $H^{(l)}$ denotes the feature matrix of the lth layer, $W^{(l)}$ represents the weights of the lth layer, and σ refers to an activation function like ReLU. The symmetric Laplacian matrix operates on the feature matrix of the lth layer along with the weights, computing the feature matrix of the $l + 1$th layer through the activation function.

Weather variable

After the propagation in the previous GCN model, the output is a two-dimensional matrix with the same shape as the feature matrix. This is elongated into a one-dimensional shape and concatenated with two weather variables: 'precipitation' and 'temperature'.

$$\hat{y} = \sigma(W_1H_1 + W_2H_2 + W_3H_3 + W_4x_1 + W_5x_2)$$

Here, $\hat{y}$ denotes the predicted bicycle demand. H_1 refers to the output of the GCN model that integrates the spatial matrix, stretched into a one-dimensional shape. Meanwhile, H_2 and H_3 represent the outputs of the GCN model encompassing the daily and weekly historical rental matrices, respectively, also stretched into one-dimensional shapes. x_1 and x_2 signify 'precipitation' and 'temperature', while W_1, W_2, W_3, W_4, and W_5 symbolize the model's weights. [11]The evaluation criterion utilized in this study was the Root Mean Square Error (RMSE) loss function.

Experimental Settings

Dataset

Bicycle flow data collected in Seoul, South Korea, was utilized for the study. All data were presented in the form of riding records containing information about rental and return stations, as well as the date of bicycle usage. For our research, the dataset sourced from the Seoul Open Data Plaza was used, spanning from March to September 2022. The training set was comprised of data from March to August, while the entire dataset for September served as the test set. The prediction granularity was set to one day. Additionally, among the total 2763 bicycle stations in Seoul, we included 2709 stations with accurately documented location information in our dataset.

Hyperparameters tuning

In this study, various hyperparameters were adjusted to enhance and optimize the performance of the developed GCN model. These hyperparameters hold significant influence over the model's structure and learning process, playing a crucial role in tuning and improving the model's performance.

The following are the settings and related explanations of key hyperparameters:

- GCN Layer: The size of the GCN model's layer, adjusted for efficient learning in the Graph Convolutional Neural Network.
- FCN Hidden Layer: The size of the hidden layer in the Fully Connected Network (FCN), adjusted to determine model density and complexity.
- Learning Rate: Determines the speed at which the model's weights are updated, utilized to regulate the model's convergence and learning speed.
- Historical Daily Rental Window Size: The window size used by the model to comprehend historical daily rental volumes, adjusted to consider daily patterns.
- Historical Weekly Rental Window Size: The window size used by the model to comprehend historical weekly rental volumes, adjusted to consider weekly patterns.
- Epochs: The number of times the learning algorithm iterates over the entire dataset, utilized to regulate model training and convergence.
- Weight Decay: A regularization parameter used to control model complexity, adjusted to prevent overfitting and improve generalization performance.

These hyperparameters significantly influenced the model's learning and predictive performance, playing a critical role in evaluating the results of this study.

The GCN model developed in this study was implemented using PyTorch and Python. Hyperparameter tuning involved researchers specifying all parameter combinations three times to identify the combination that resulted in the lowest average RMSE value for the test set. To reduce the number of parameter combinations, several measures were taken. The GCN's hidden layer count included parameters of up to 4 [19], while the FCN hidden layer count was manually set to 2 after identifying no significant difference when the hidden layer count exceeded 2. The sizes for the historical daily and weekly rental windows were chosen based on criteria outlined in previous literature [11], selecting daily rental window sizes from 3 to 5 days and weekly rental window sizes from 1 to 5 weeks.

Table 2. The optimal hyperparameter combination

GCN hidden layer	2
FCN hidden layer	2
Day	3
Week	4
Epoch	300
Learning rate	0.001

The table represents the optimal combination of hyperparameters. Both the GCN and FCN models employed the rectified linear unit (ReLU) as the activation function, and Adam Optimizer was utilized as the optimizer.

Weather variable

Furthermore, hyperparameter tuning for weather variables was undertaken. Variables such as precipitation (mm), maximum temperature (℃), average temperature (℃), and minimum temperature (℃) were obtained, and the impracticality of measuring all possible combinations was confronted. Therefore, following the precedent literature, the precipitation variable was initially included, [11] and subsequently, temperature variables were definitively incorporated. Predictive performance was then compared based on the presence or absence of other variables. The outcomes revealed that the introduction of variables beyond precipitation (mm) and average temperature (℃) either yielded similar predictive performance or, in some cases, exhibited lower performance. Consequently, a decision was made to include only the precipitation (mm) and average temperature (℃) variables in our model. This segment addresses a subset of the hyperparameter optimization process for our model, specifically focusing on weather variables.

Results

Comparative analysis

In this study, a comparative analysis was conducted to assess the performance of the GCN-pro model against other models. Differences in performance were investigated among models utilizing distinct types of data for demand prediction. Specifically, evaluations were made of models based on time series data, including LSTM [18], CNN, SARIMAX, and XG-Boost, compared to our GCN-pro model, which integrates spatial data. Additionally, the involvement of the GCN-UP model, leveraging graph data in previous research, was considered. [11] The GCN-pro model outperformed all other models in terms of performance. Excluding GCN-pro, the other models, namely CNN, LSTM, GCN-UP, XGBoost, and ARIMA, demonstrated suboptimal performance in descending order. The prior literature indicated that GCN-UP exhibited RMSE values comparable to those of the LSTM model, confirming its consistent reproducibility in terms of performance. [11]

Table 3. Comparative table with each models

Model	**GCN-pro**	**GCN-UP**	**LSTM**	**CNN**	**XGboost**	**ARIMA**
RMSE	14.65	23.35	23.3	18.9	24.5	31.7

GCN-pro vs CNN

In the comparison between GCN-pro and CNN models, the figure illustrates the model with the best performance among the comparative models, namely the CNN model and GCN-pro. Maintaining prediction performance as the date extends further from the train set is a crucial consideration in demand prediction models. Therefore, the study compared the actual and predicted values of both models across the entire September test set. For the GCN-pro model, it accurately predicted rental quantities until around September 20th but struggled to predict actual rental quantities beyond that date. Particularly, before September 20th, the GCN-pro model consistently demonstrated superior ability compared to CNN in capturing daily trends and predicting demand. However, during the period from September 9th to 12th, the GCN-pro model exhibited suboptimal performance despite the proximity to the train set dates. This discrepancy is interpreted as a consequence of the exceptional circumstances during the Chuseok holiday period, where bicycle usage patterns deviated significantly from normal days.

Despite these limitations, GCN-pro showcased better alignment with actual values compared to CNN.

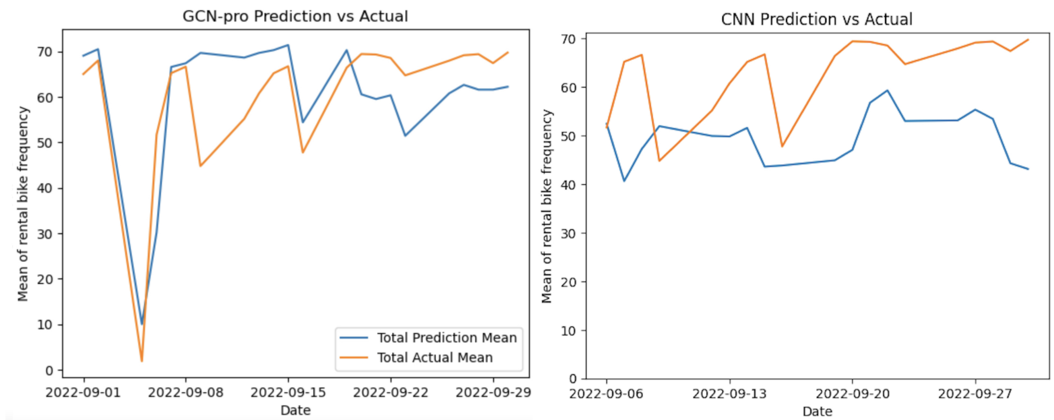

Fig 2. Predicted graphs for the top 3 stations in rental volume using GCN-pro

Prediction in Station-level

At the station level, the performance of the GCN-pro model in predicting bicycle demand is a crucial aspect. Predicting demand for bicycles at the level of individual stations is identified as a key solution to address the imbalance issue in public bicycle systems, a prominent challenge in current bike-sharing discussions. The GCN-pro model tailors its predictions to the demand at each station, covering a total of 2,709 stations. Fig2 illustrates the prediction results for the three stations with the highest bicycle usage.

The GCN-pro model demonstrates robust performance, effectively capturing sudden changes in the actual rental trends for individual stations. However, it is noteworthy that during the period from September 9th to 12th, corresponding to the Chuseok holiday, the model encounters challenges in accurately predicting the actual values. This discrepancy is interpreted as a result of the unique patterns of bicycle rentals during this period, characterized by the distinctive behaviors associated with the Chuseok holiday, a major traditional festival in Korea. The Figure 4 presented below delineates the RMSE values across various stations in Seoul city, categorized by color, with red indicating higher RMSEs and blue representing lower ones. Among the stations with the highest RMSE is 'Shinhan Financial Investment Bicycle Rental Station', a location characterized by a complex interplay of factors influencing bicycle rental volumes. Directly across the street lies Yeouido Park, and the vicinity encompasses residential areas, a bus stop, and the Yeouido Transfer Center. Additionally, its proximity to the Han River and major bridges contributes to its status as a high-traffic area. These multifaceted influences can complicate prediction efforts.

Discussion

This study introduced an approach to bicycle demand prediction that incorporates spatial characteristics specific to each station, a facet not addressed in prior research. The results revealed superior performance compared to existing GCN models and other basic models. The study elucidated the relationships between stations, utilizing a GCN model that incorporates information on the temporal past rental volumes in a time series. To enhance the model's capability in solving classification problems, a

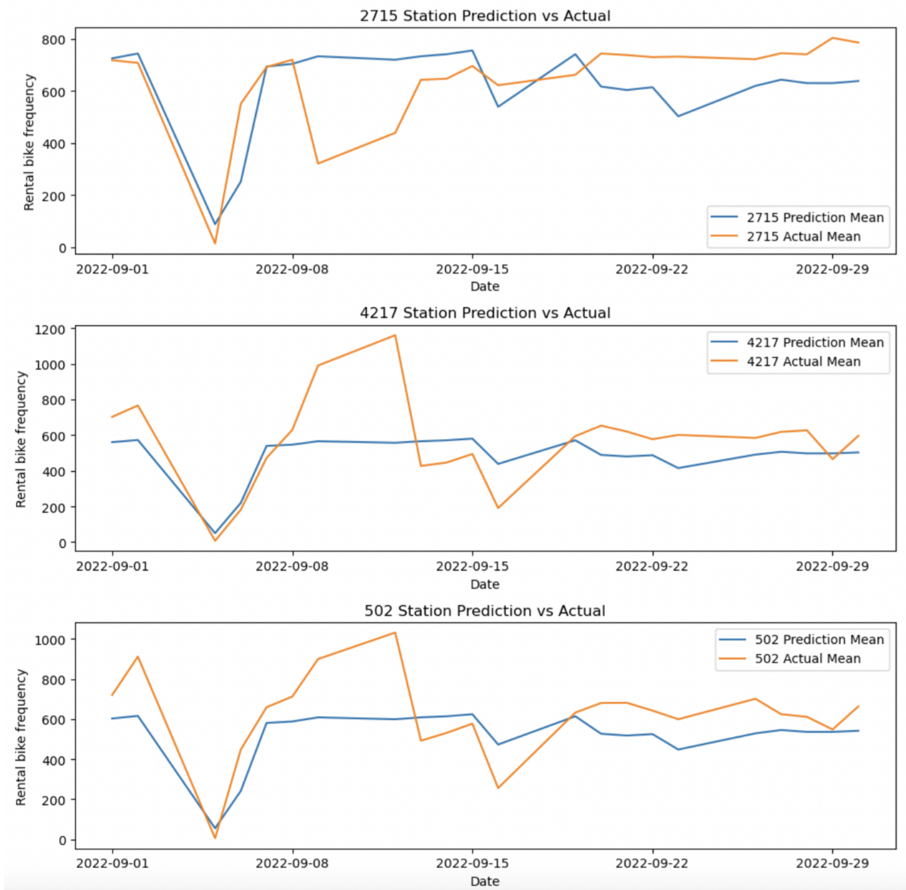

Fig 3. Predicted graphs for the top 3 stations in rental volume using GCN-pro

combination of GCN and FCN models was employed. Additionally, the impact of spatial features on actual rental quantities was tested using the Kruskal-Wallis test. The results identified 11 out of 15 spatial features as significant contributors to rental demand, with these features closely aligning with spatial elements influencing bicycle demand proposed in previous studies.

While Graph Convolutional Networks (GCNs) have shown promising results in various applications, they exhibit certain limitations that must be acknowledged:

- High Computational Cost: GCNs often involve substantial computational expenses, primarily due to the complex nature of graph convolution operations. This complexity becomes more pronounced as the size and connectivity of the graph increase, posing challenges in scaling the model efficiently for larger graphs.

- Difficulty in Predicting Large Fluctuations in Rental Volume: In the context of rental demand forecasting, GCNs demonstrate limitations in accurately predicting scenarios with significant fluctuations in rental volume. The model's performance tends to degrade with the increase in variability of the rental demand, indicating a potential shortfall in capturing highly dynamic patterns.

- Limited Number of Hidden Layers Reduces Pattern Recognition Capability: Unlike other deep learning models that leverage a large number of hidden layers to uncover patterns in extensive datasets, GCNs, particularly the GCN-pro model, are restricted by having only two hidden layers. This limitation necessitates the

Fig 4. Seoul Station RMSE Heat-map: Red for High, Green-Blue for Low Errors

selection of statistically significant variables as inputs to the model. Incorporating only the most relevant and impactful variables has been observed to enhance the performance of GCN-pro, aligning with the model's constrained capacity to process and learn from complex, multi-dimensional data.

Conclusion

The Graph Convolutional Network pro (GCN-pro) model was developed for demand prediction using rental volume, weather, and spatial data. The nodes in GCN-pro represent docking stations, and predictions utilized spatial variables within a radius of approximately 500 meters for each station. A comprehensive analysis was conducted to assess the model's performance compared to GCN-UP, LSTM, CNN, XGBoost, and ARIMA. Ultimately, GCN-pro exhibited superior performance compared to the other models, implying that structuring the model as a graph, rather than relying solely on the general flow of time, is more suitable. Additionally, the incorporation of node-specific features contributes to more accurate predictions.

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