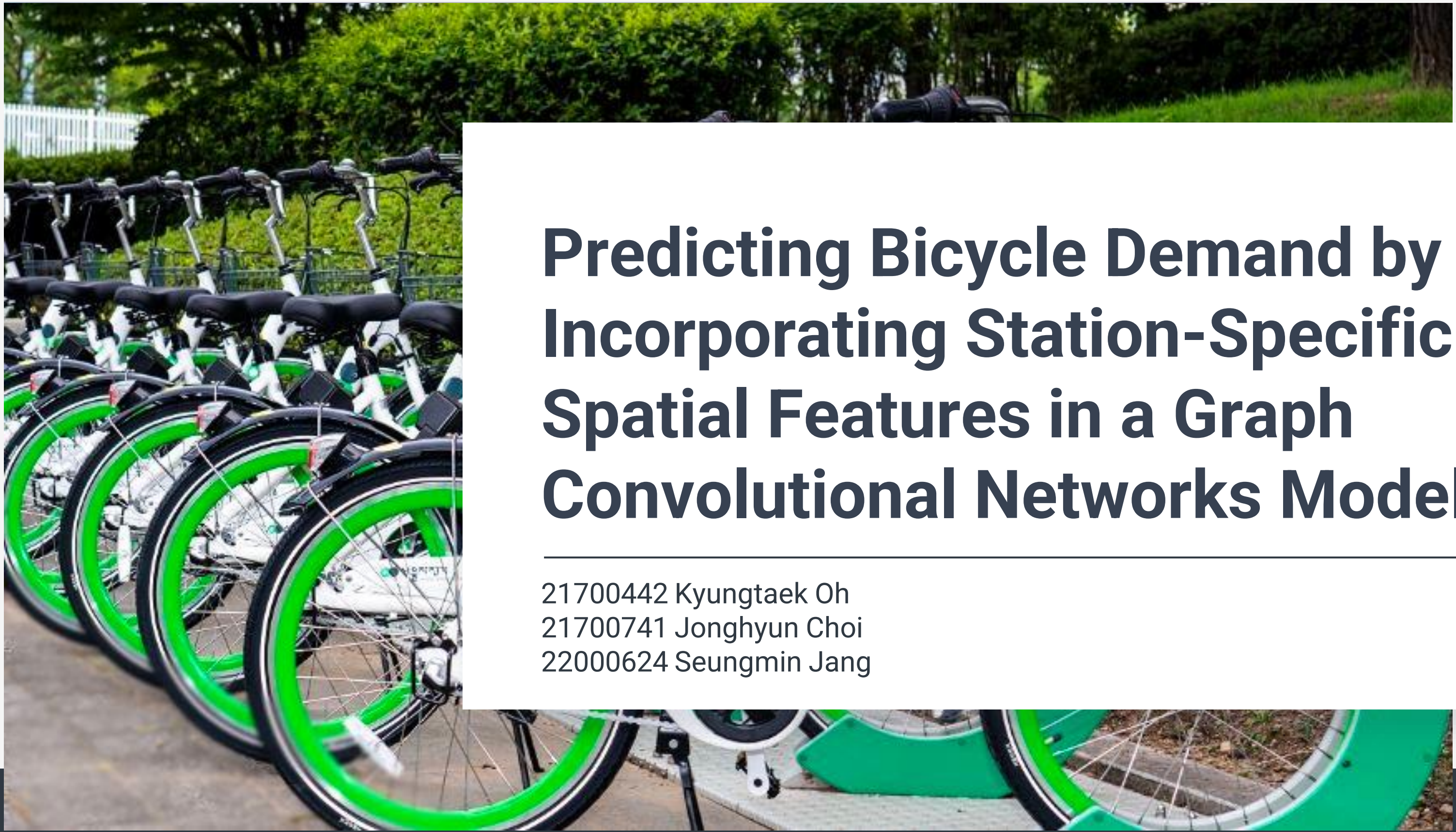

Predicting Bicycle Demand by Incorporating Station-Specific Spatial Features in a Graph Convolutional Networks Model

21700442 Kyungtaek Oh
21700741 Jonghyun Choi
22000624 Seungmin Jang

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01

Introduction

History of our doing

History of our doing

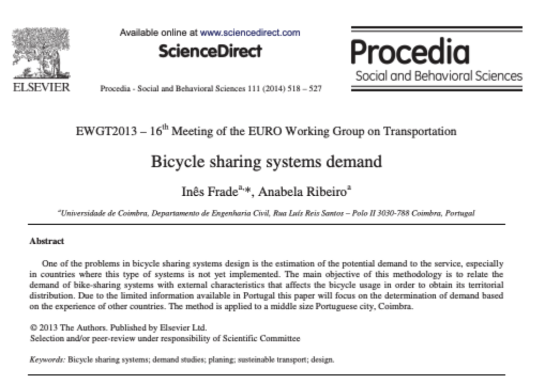
https://www.kihoilbo.co.kr/news/articleView.html?idxno=1028799
https://news.tf.co.kr/read/ptoday/1693773.htm
https://m.khan.co.kr/national/national-general/article/202203290858011
https://news.sbs.co.kr/news/endPage.do?news_id=N1006236394

Selection of topics

Predict the bike rental rate

History of our doing

Previous research : Spatio–temporal properties



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Social and Behavioral Sciences

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Procedia - Social and Behavioral Sciences 111 (2014) 518 – 527

EWGT2013 – 16th Meeting of the EURO Working Group on Transportation

Bicycle sharing systems demand

Inês Frade[a,*], Anabela Ribeiro[a]

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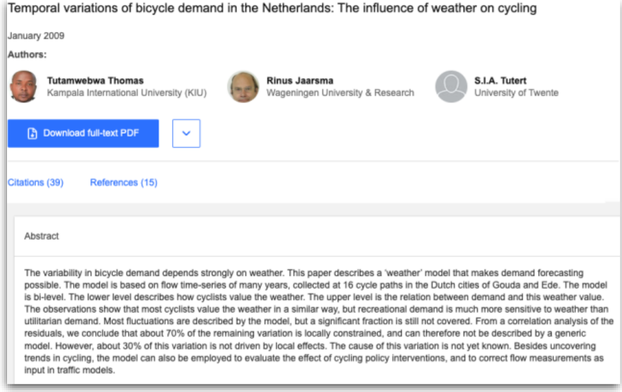
Abstract

One of the problems in bicycle sharing systems design is the estimation of the potential demand to the service, especially in countries where this type of systems is not yet implemented. The main objective of this methodology is to relate the demand of bike-sharing systems with external characteristics that affects the bicycle usage in order to obtain its territorial distribution. Due to the limited information available in Portugal this paper will focus on the determination of demand based on the experience of other countries. The method is applied to a middle size Portuguese city, Coimbra.

Keywords: Bicycle sharing systems; demand studies; planing; susteinable transport; design.

weather, time

Multi Regression



Temporal variations of bicycle demand in the Netherlands: The influence of weather on cycling

January 2009

Authors:

Tutamwebwa Thomas
Kampala International University (KIU)

Rinus Jaarsma
Wageningen University & Research

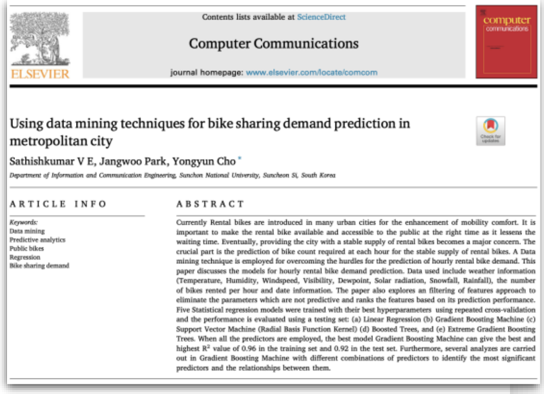
S.I.A. Tutert
University of Twente

Abstract

The variability in bicycle demand depends strongly on weather. This paper describes a 'weather' model that makes demand forecasting possible. The model is based on flow time-series of many years, collected at 16 cycle paths in the Dutch cities of Gouda and Ede. The model is bi-level. The lower level describes how cyclists value the weather. The upper level is the relation between demand and this weather value. The observations show that most cyclists value the weather in a similar way, but recreational demand is much more sensitive to weather than utilitarian demand. Most fluctuations are described by the model, but a significant fraction is still not covered. From a correlation analysis of the residuals, we conclude that about 70% of the remaining variation is locally constrained, and can therefore not be described by a generic model. However, about 30% of this variation is not driven by local effects. The cause of this variation is not yet known. Besides uncovering trends in cycling, the model can also be employed to evaluate the effect of cycling policy interventions, and to correct flow measurements as input in traffic models.

weather, time, location(purpose)

Multi Regression



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ELSEVIER

Using data mining techniques for bike sharing demand prediction in metropolitan city

Sathishkumar V E, Jangwoo Park, Yongyun Cho *

Department of Information and Communication Engineering, Sunchon National University, Suncheon Si, South Korea

ARTICLE INFO

Keywords:
Data mining
Predictive analytics
Public bikes
Regression
Bike sharing demand

ABSTRACT

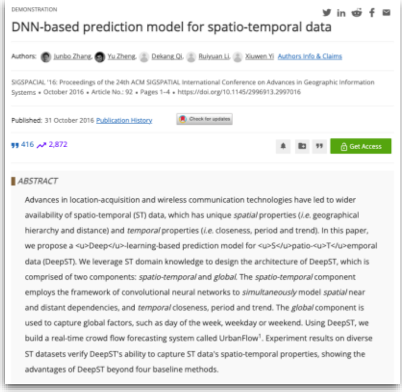
Currently Rental bikes are introduced in many urban cities for the enhancement of mobility comfort. It is important to make the rental bike available and accessible to the public at the right time as it lessens the waiting time. Eventually, providing the city with a stable supply of rental bikes becomes a major concern. The crucial part is the prediction of bike count required at each hour for the stable supply of rental bikes. A Data mining technique is employed for overcoming the hurdles for the prediction of hourly rental bike demand. This paper discusses the models for hourly rental bike demand prediction. Data used include weather information (Temperature, Humidity, Windspeed, Visibility, Dewpoint, Solar radiation, Snowfall, Rainfall), the number of bikes rented per hour and date information. The paper also explores an filtering of features approach to eliminate the parameters which are not predictive and ranks the features based on its prediction performance. Five Statistical regression models were trained with their best hyperparameters using repeated cross-validation and the performance is evaluated using a testing set: (a) Linear Regression (b) Gradient Boosting Machine (c) Support Vector Machine (Radial Basis Function Kernel) (d) Boosted Trees, and (e) Extreme Gradient Boosting Trees. When all the predictors are employed, the best model Gradient Boosting Machine can give the best and highest R^2 value of 0.96 in the training set and 0.92 in the test set. Furthermore, several analyzes are carried out in Gradient Boosting Machine with different combinations of predictors to identify the most significant predictors and the relationships between them.

weather

LM, GBM, SVM, BT, XGBTree

History of our doing

Previous research : Deep Learning approaches



DEMONSTRATION

DNN-based prediction model for spatio-temporal data

Authors: Junbo Zhang, Yu Zheng, Dekang Qi, Ruiyuan Li, Xiuwen Yi Authors Info & Claims

SIGSPACIAL '16: Proceedings of the 24th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems • October 2016 • Article No.: 92 • Pages 1–4 • https://doi.org/10.1145/2996913.2997016

Published: 31 October 2016 Publication History

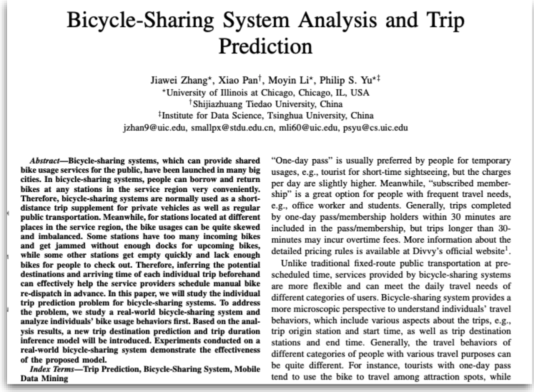
416 2,872

Get Access

ABSTRACT

Advances in location-acquisition and wireless communication technologies have led to wider availability of spatio-temporal (ST) data, which has unique *spatial* properties (*i.e.* geographical hierarchy and distance) and *temporal* properties (*i.e.* closeness, period and trend). In this paper, we propose a <u>Deep</u>-learning-based prediction model for <u>S</u>patio-<u>T</u>emporal data (DeepST). We leverage ST domain knowledge to design the architecture of DeepST, which is comprised of two components: *spatio-temporal* and *global*. The *spatio-temporal* component employs the framework of convolutional neural networks to *simultaneously* model *spatial* near and distant dependencies, and *temporal* closeness, period and trend. The *global* component is used to capture global factors, such as day of the week, weekday or weekend. Using DeepST, we build a real-time crowd flow forecasting system called UrbanFlow[1]. Experiment results on diverse ST datasets verify DeepST's ability to capture ST data's spatio-temporal properties, showing the advantages of DeepST beyond four baseline methods.

CNN



Bicycle-Sharing System Analysis and Trip Prediction

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***Abstract*—Bicycle-sharing systems, which can provide shared bike usage services for the public, have been launched in many big cities. In bicycle-sharing systems, people can borrow and return bikes at any stations in the service region very conveniently. Therefore, bicycle-sharing systems are normally used as a short-distance trip supplement for private vehicles as well as regular public transportation. Meanwhile, for stations located at different places in the service region, the bike usages can be quite skewed and imbalanced. Some stations have too many incoming bikes and get jammed without enough docks for upcoming bikes, while some other stations get empty quickly and lack enough bikes for people to check out. Therefore, inferring the potential destinations and arriving time of each individual trip beforehand can effectively help the service providers schedule manual bike re-dispatch in advance. In this paper, we will study the individual trip prediction problem for bicycle-sharing systems. To address the problem, we study a real-world bicycle-sharing system and analyze individuals' bike usage behaviors first. Based on the analysis results, a new trip destination prediction and trip duration inference model will be introduced. Experiments conducted on a real-world bicycle-sharing system demonstrate the effectiveness of the proposed model.**

***Index Terms*—Trip Prediction, Bicycle-Sharing System, Mobile Data Mining**

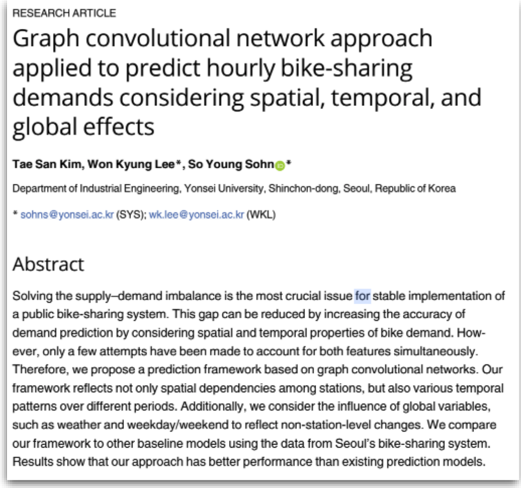
"One-day pass" is usually preferred by people for temporary usages, e.g., tourist for short-time sightseeing, but the charges per day are slightly higher. Meanwhile, "subscribed membership" is a great option for people with frequent travel needs, e.g., office worker and students. Generally, trips completed by one-day pass/membership holders within 30 minutes are included in the pass/membership, but trips longer than 30-minutes may incur overtime fees. More information about the detailed pricing rules is available at Divvy's official website[1].

Unlike traditional fixed-route public transportation at pre-scheduled time, services provided by bicycle-sharing systems are more flexible and can meet the daily travel needs of different categories of users. Bicycle-sharing system provides a more microscopic perspective to understand individuals' travel behaviors, which include various aspects about the trips, e.g., trip origin station and start time, as well as trip destination stations and end time. Generally, the travel behaviors of different categories of people with various travel purposes can be quite different. For instance, tourists with one-day pass tend to use the bike to travel among attraction spots, while

ResNet

History of our doing

Previous research : Graph Convolutional Network(GCN)



RESEARCH ARTICLE

Graph convolutional network approach applied to predict hourly bike-sharing demands considering spatial, temporal, and global effects

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Abstract

Solving the supply–demand imbalance is the most crucial issue for stable implementation of a public bike-sharing system. This gap can be reduced by increasing the accuracy of demand prediction by considering spatial and temporal properties of bike demand. However, only a few attempts have been made to account for both features simultaneously. Therefore, we propose a prediction framework based on graph convolutional networks. Our framework reflects not only spatial dependencies among stations, but also various temporal patterns over different periods. Additionally, we consider the influence of global variables, such as weather and weekday/weekend to reflect non-station-level changes. We compare our framework to other baseline models using the data from Seoul's bike-sharing system. Results show that our approach has better performance than existing prediction models.

Structure : Node & Edge
Data : Diverse spatial features & Various temporal patterns
Consider : global variables such as weather and weekdays

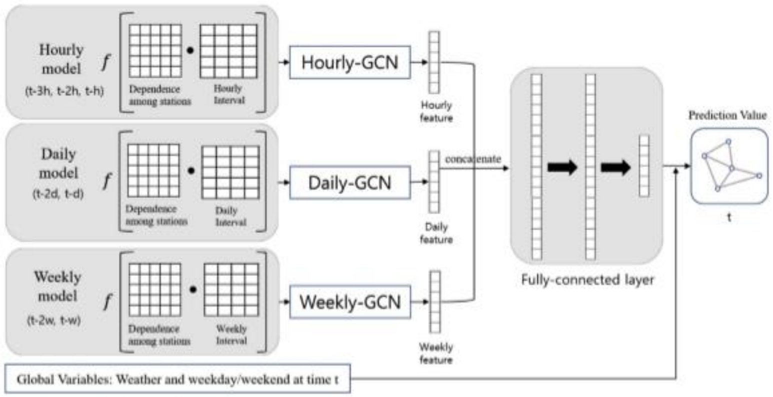


Fig 1. Framework of proposed GCN.

History of our doing

Previous research : Graph Convolutional Network(GCN)

Limitation & Differentiation

History of our doing

Project Goal

Using the **GCN-pro** model trained on **spatial**, **temporal**, and **historical rental data**, predict the **demand for each bike-sharing station**

History of our doing

Data : Collecting (Usage information)

Data	Feature	Data type	Information
Public Bicycle Usage Information	**Rental Station Number**	int64	The identification number of the rental station
	Return Station Number	object	The identification number of the return station

History of our doing

Data : Collecting (Spatial data)

Data	Feature	Data type	Information
Spatial data	**Number of nearby bus stops**	int64	Number of bus stops within 500m
	Number of nearby subway stations	int64	Number of subway stations within 500m
	Number of nearby schools	int64	Number of schools within 500m
	Number of nearby apartment households	int64	Number of apartment households within 500m
	Number of nearby cultural facilities	int64	Number of cultural facilities within 500m
	Number of nearby universities	int64	Number of universities within 500m
	Number of nearby large academies	int64	Number of large academies within 500m

History of our doing

(A) Urban area
(B) Riverside area

Data	Feature	Data type	Information
Spatial data	**(A) Non-segregated shared road**	int64	Road shared by bicycles and other vehicles without a designated separation
	(A) Bicycle-exclusive road	int64	Road exclusively designated for bicycles
	(A) Segregated shared road	int64	Road shared by bicycles and other vehicles with a designated separation
	(A) Bicycle-exclusive lane	int64	A lane exclusively designated for bicycles within a road
	(B) Bicycle-exclusive road	int64	Road exclusively designated for bicycles
	(B) Segregated shared road	int64	Road shared by bicycles and other vehicles with a designated separation
	(B) Non-segregated shared road	int64	Road shared by bicycles and other vehicles without a designated separation
	(A) Bicycle priority road	int64	Road where bicycles have priority over other vehicles

History of our doing

Data : Collecting (Time series data)

Data	Feature	Data type	Information
Time series data	**Precipitation (mm)**	float	The amount of water, in millimeters, that falls as rain or snow during a specific period
	Maximum Temperature (℃)	float	The highest temperature recorded during a given period
	Average Temperature (℃)	float	The mean temperature calculated over a specific timeframe
	Minimum Temperature (℃)	float	The lowest temperature observed within a designated period
	Diurnal Range	float	The difference between the maximum and minimum temperatures in a single day

History of our doing

Data : Collecting (Time series data)

Data	Feature	Data type	Information
Time series data	**Average Humidity (%rh)**	float	The mean level of moisture in the air, expressed as a percentage of relative humidity
	Sunshine Duration (%)	float	The percentage of time during which the sun is visible within a specified timeframe
	Average Wind Speed (m/s)	float	The mean speed of the wind measured in meters per second
	Maximum Wind Speed (m/s)	float	The highest wind speed recorded during a specific period

History of our doing

Data : Preprocessing

Usage information

Make adjacency matrix

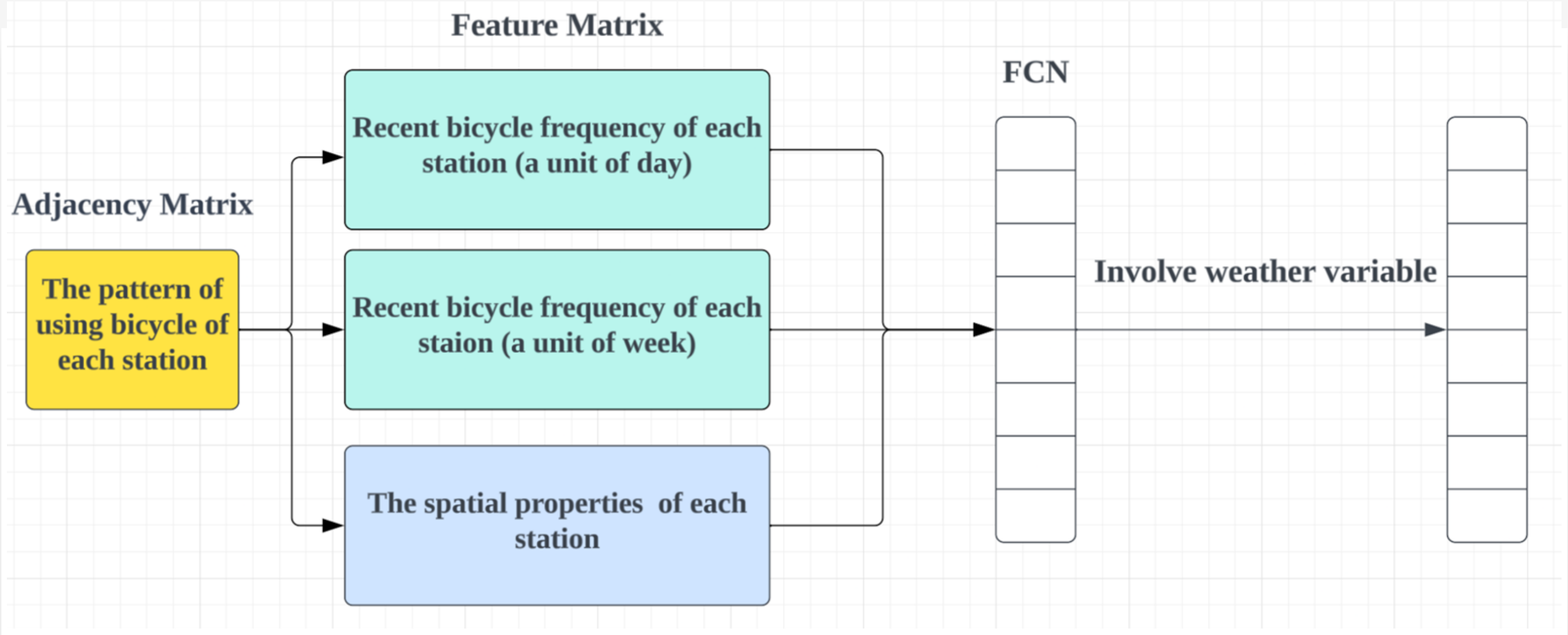
Spatial data

Count the number of data points within 500 meters by verifying latitude and longitude

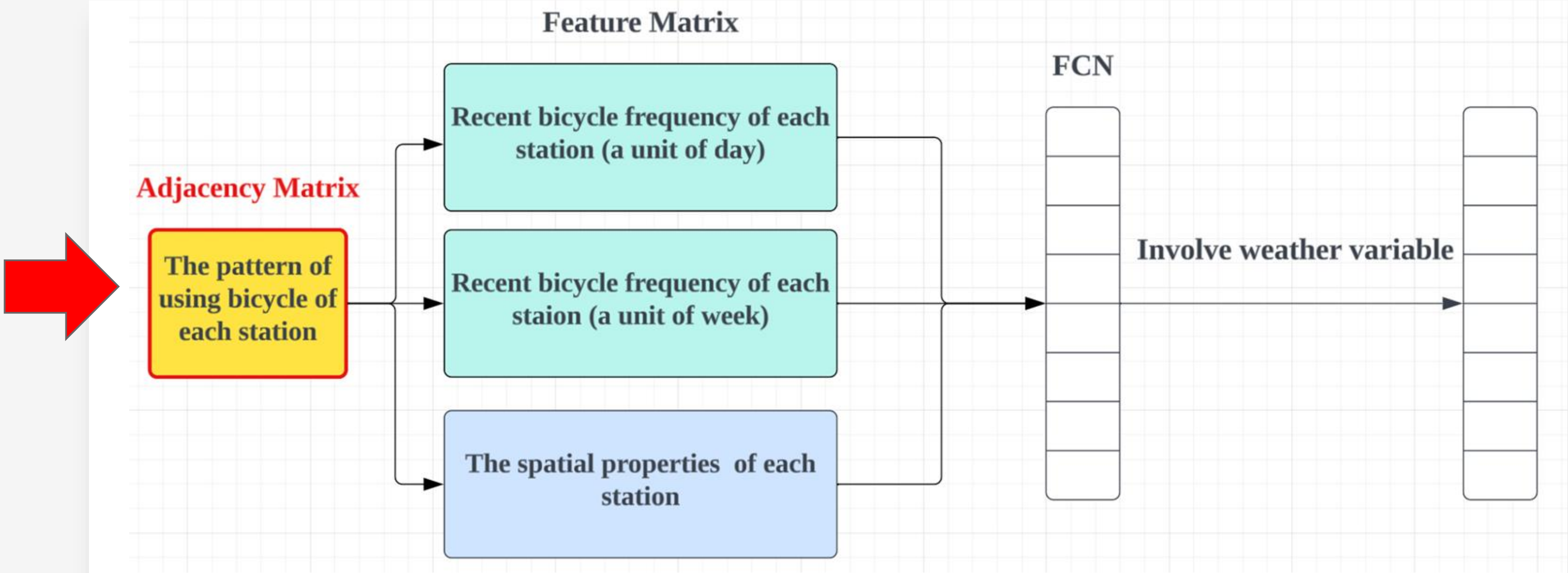
Time series data

Organize the data on a daily basis with Seoul as the reference point

Our Proposed Framework - GCN-pro



1. Construction of Adjacency Matrix



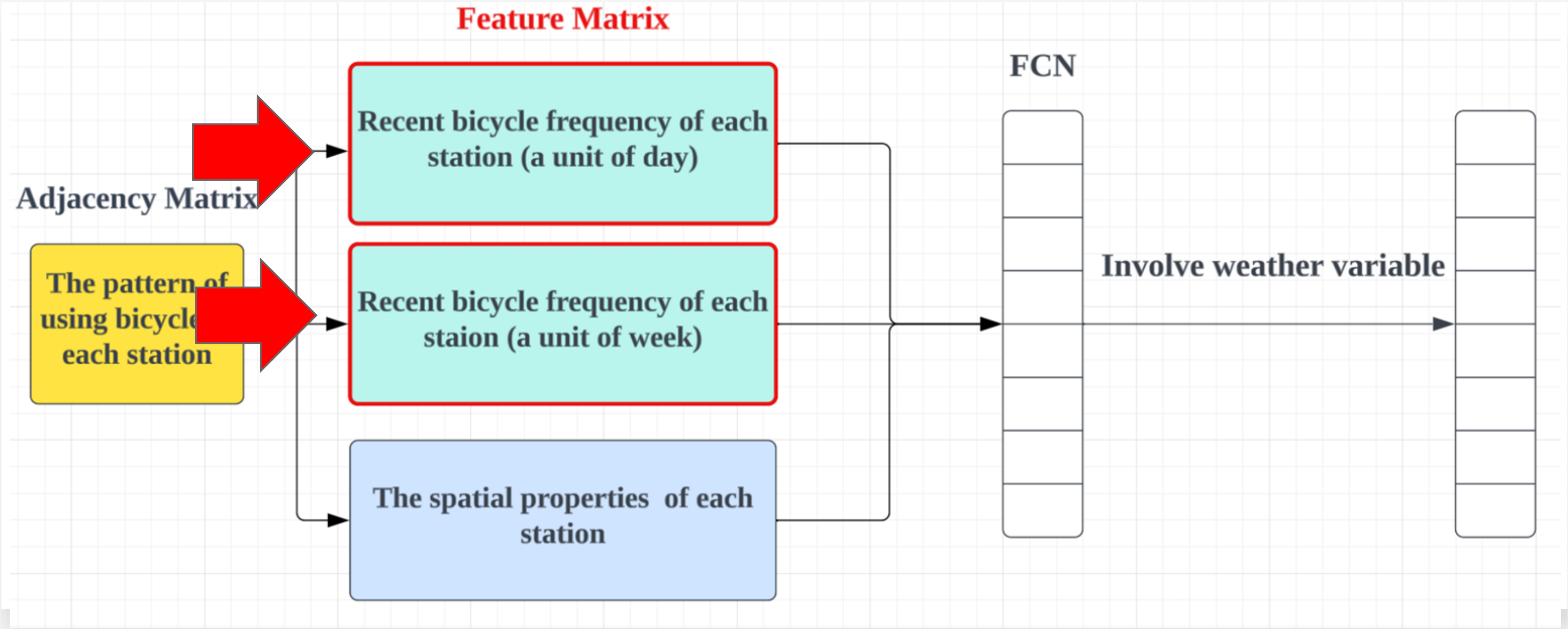
1. Construction of Adjacency Matrix

	102	103	104	105	106
102	3322.0	887.0	688.0	276.0	563.0
103	752.0	2887.0	525.0	367.0	943.0
104	1032.0	575.0	1063.0	197.0	318.0
105	320.0	321.0	152.0	765.0	336.0
106	847.0	1243.0	195.0	332.0	2916.0
...	...	...	...	...	...

	102	103	104	105	106
102	0.109529	0.029245	0.022684	0.009100	0.018562
103	0.024794	0.095186	0.017310	0.012100	0.031091
104	0.034026	0.018958	0.035048	0.006495	0.010485
105	0.010551	0.010584	0.005012	0.025223	0.011078
106	0.027926	0.040983	0.006429	0.010946	0.096142
...	...	...	...	...	...

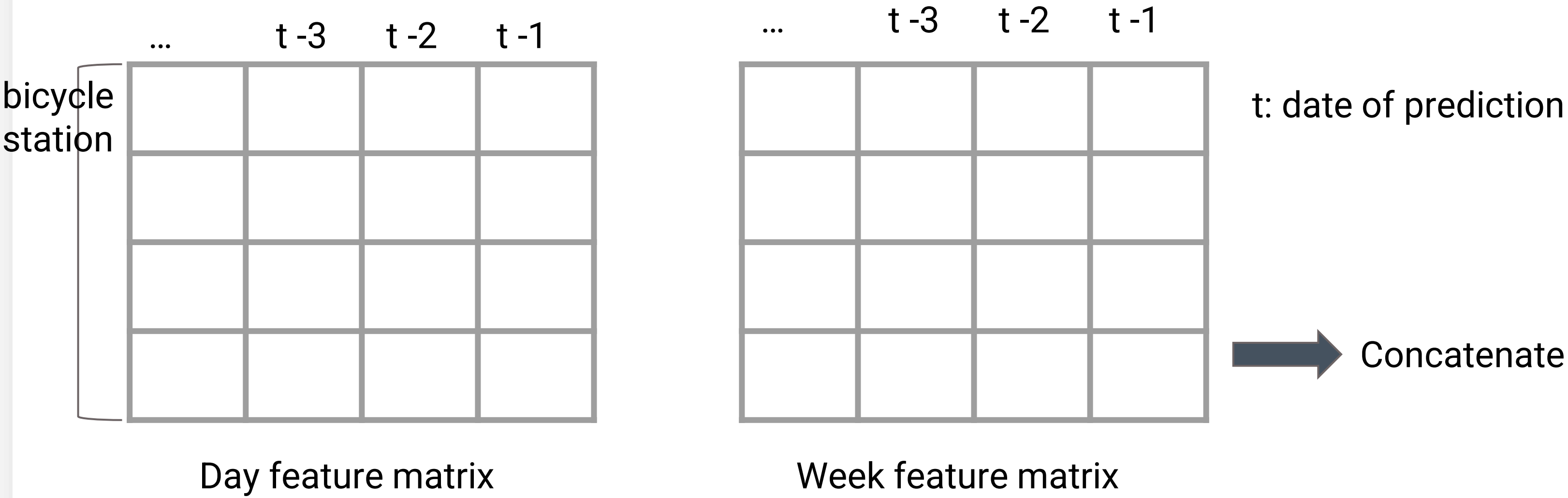
$$L^{sym} = D^{-\frac{1}{2}} L D^{-\frac{1}{2}}$$

2. Construction of Temporal Rental Activity Matrix

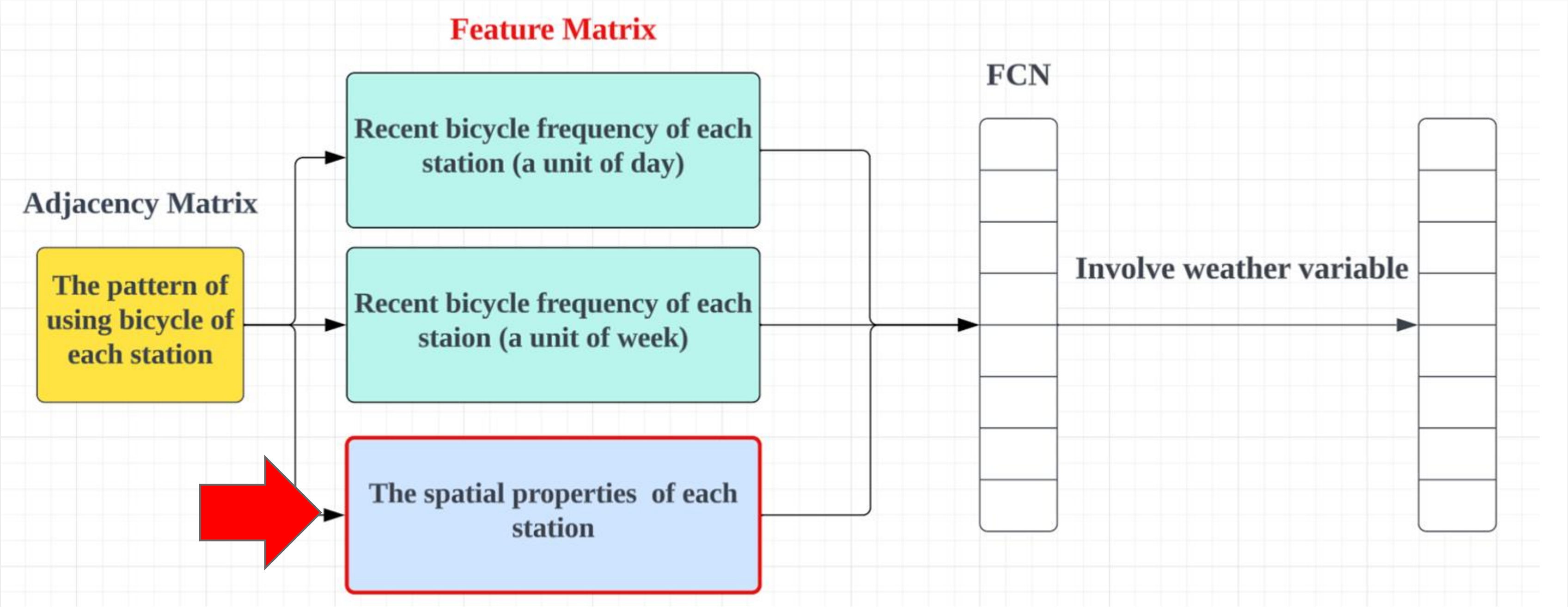


2. Construction of Temporal Rental Activity Matrix

Structure of previous rental matrix



3. Formation of Spatial Matrix Representation



3. Formation of Spatial Matrix Representation

	자전거대여소 번호	인근 버스정류장 개수	인근 지하철역 개수	인근 학교 수	인근 아파트 세대수	인근 문화시설 수	인근 대학교 개수	인근 대형학원 개수	(A)비분리형 겸용도로	(A)자전거 전용도로	(A)분리형 겸용도로	(A)자전거 전용차로	(B)자전거 전용도로	(B)분리형 겸용도로	(B)비분리형 겸용도로	(A)자전거 우선도로
0	301	23	1	7	894	8	1	0	0	0	0	2	0	0	0	2
1	302	24	1	6	150	6	0	0	0	0	1	5	0	0	0	3
2	303	33	2	1	150	14	0	0	1	2	4	3	0	0	0	6
3	305	48	2	0	0	17	0	0	1	2	3	7	0	0	0	6
4	307	25	1	7	150	20	0	0	1	0	1	0	0	0	0	7
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2714	3698	39	1	2	8440	0	0	0	6	0	0	0	0	0	0	0
2715	3699	24	1	1	7154	0	0	0	2	7	5	0	0	0	0	0
2716	3700	6	1	1	1009	1	0	0	5	0	3	0	0	1	0	0
2717	3701	10	0	0	438	0	0	0	0	0	0	0	0	0	0	0
2718	4951	22	0	3	1455	0	0	0	0	0	0	0	0	0	0	0

2719 rows × 16 columns

Goal of our project

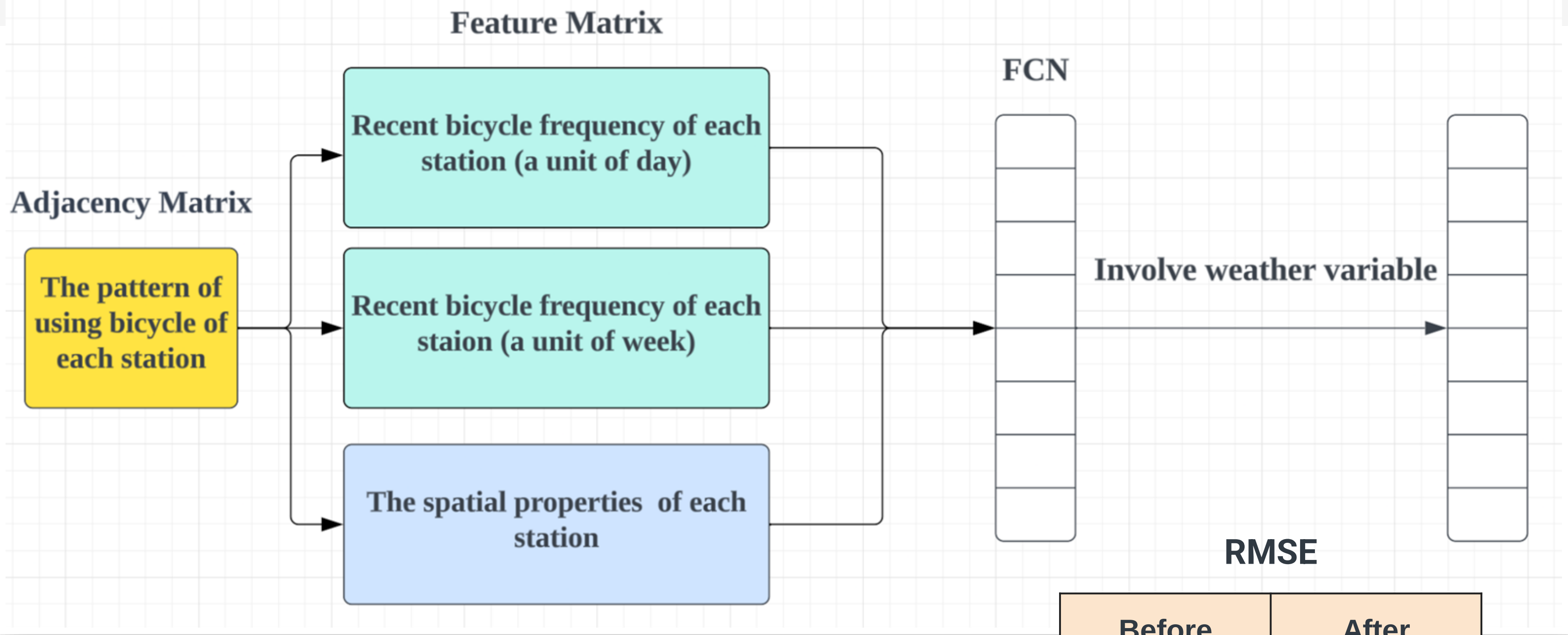
Task	Description	Details
1	Optimize Hyperparameters	GCN-PRO, XGBoost, LSTM, ARIMA
2	Feature Selection	Investigate the importance of variables using recursive feature elimination
3	Data-driven Decision Making	Validating applicability with 2023 data
4	Analyze Results	Compare which rentals GCN predicts poorly and which it predicts well
5	Journal	Plan to submit a paper to the PLOS ONE journal website

02

Process after Mid-presentation

Revised Proposed Framework
Transition of Training and Testing Datasets
Hyperparameter tuning
Prediction by station
Comparative RMSE

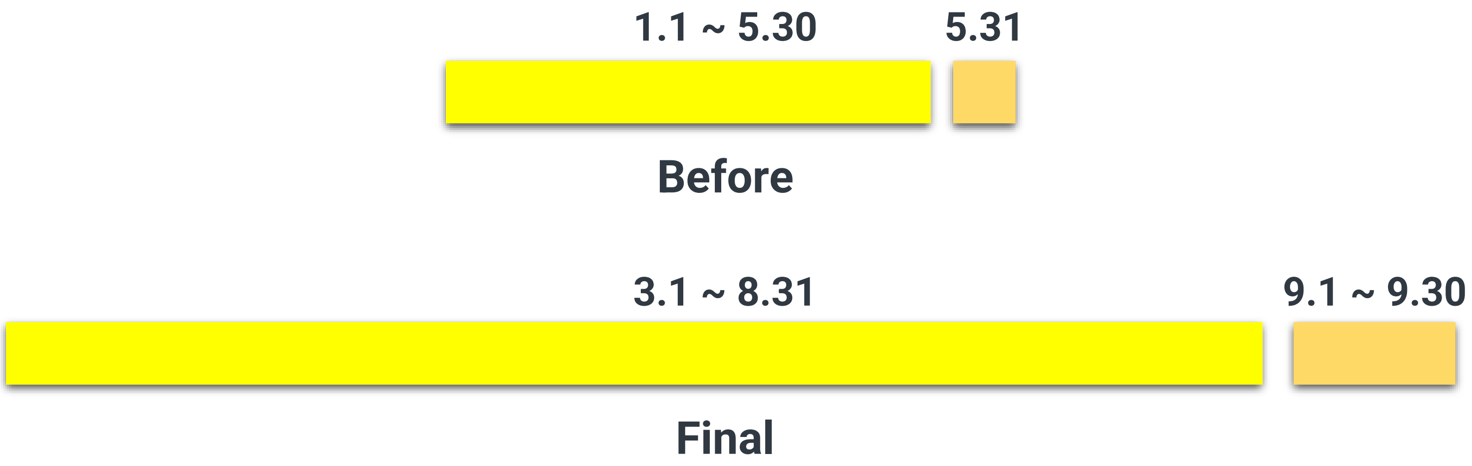
1. Revised Proposed Framework - GCN-pro



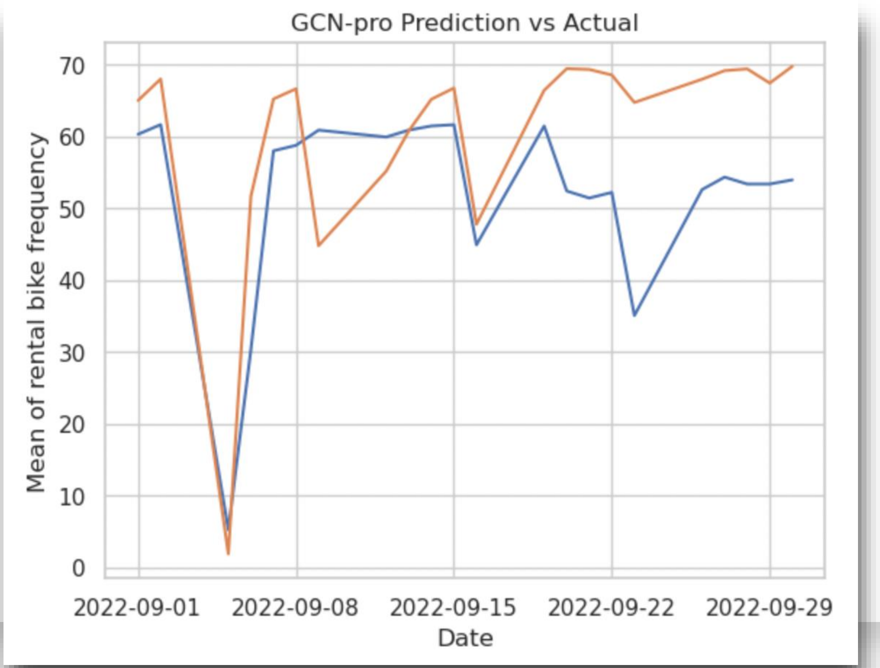
RMSE

Before	After
26.43	23.23

2. Transition of Training and Testing Datasets



2. Transition of Training and Testing Datasets



RMSE	14.65

Orange: Prediction value
Blue : Actual value

3. Investigating the Influence of Spatial Features

1. Divide 4 groups by the number of spatial feature

→ Investigate the difference of each group

q1	q2	q3	q4

2. Null hypothesis:

→ There is no difference in volume in groups with different

number of spatial characteristics

→ **Kruskal-Wallis Analysis, p-value < 0.05**

3. Investigating the Influence of Spatial Features

Result

Spatial Feature	p - value
인근 버스정류장 개수	7.72e-18
인근 지하철역 개수	7.74e-15
인근 학교 수	0.01
인근 아파트 세대수	0.04
인근 문화시설 수	0.30
인근 대학교 개수	0.83
인근 대형학원 개수	0.18

(A)비분리형 겸용도로	4.66e-08
(A)자전거 전용도로	1.86e-24
(A)분리형 겸용도로	0.0003
(A)자전거 전용차로	6.15e-05
(B)자전거 전용도로	1.55e-05
(B)분리형 겸용도로	0.001
(B)비분리형 겸용도로	0.46
(A)자전거 우선도로	7.29e-10

3. Investigating the Influence of Spatial Features

Result

	Before	After
Significant Features(11)	O	O
Non-significant features(4)	O	X
RMSE	23.45	14.65

4. Hyperparameter tuning of GCN-pro

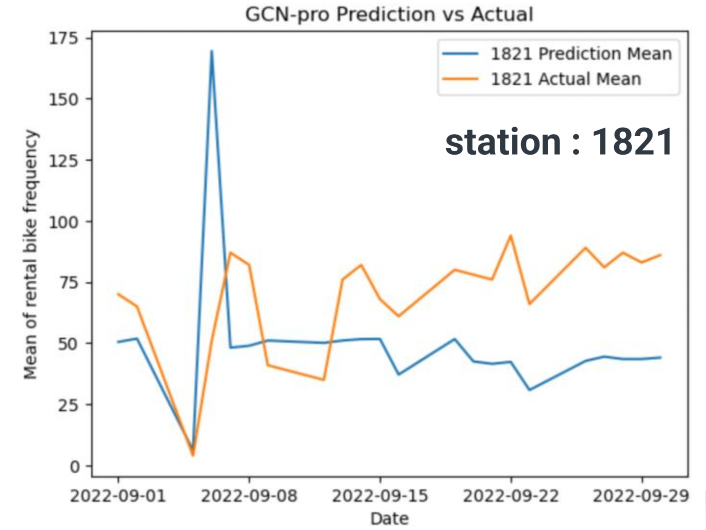
Hyperparameter	Combination
GCN hidden layer	(0, 2)
FCN hidden layer	2
과거 일별 대여량	(3, 4, 5)
과거 주별 대여량	(1 ~ 3)
Learning rate	(0.01, 0.05, 0.001)
Weight decay	(0, 5e-4, 5e-5)
epoch	(300, 400, 500)

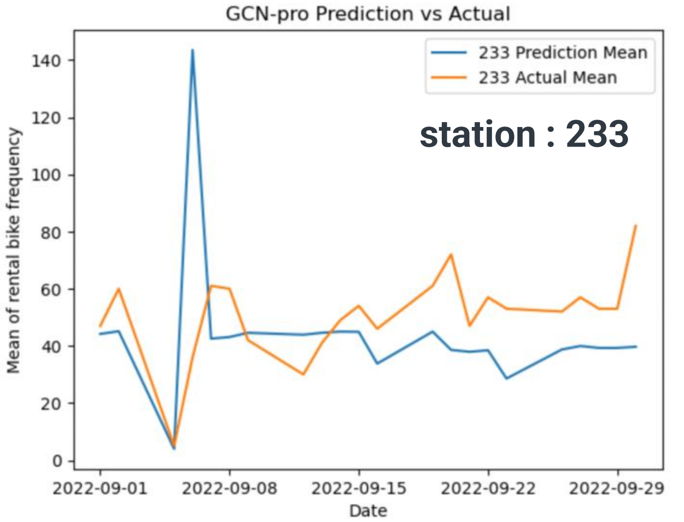
Hyperparameter	Best Combination
GCN hidden layer	2
FCN hidden layer	2
과거 일별 대여량	3
과거 주별 대여량	4
Learning rate	0.001
Weight decay	0
epoch	300

\+ Precipitation, Average Temperature

5. Prediction by station - level

Loss function: Calculate the mean of station error → Calculate the each station error





6. Hyperparameter tuning of Comparative model

LSTM

Hyper parameter	Combination	**Best combination**
n hidden features	(10, 20, 30)	20
num_layers	(1, 2, 3)	3
dropout	(0, 0.2, 0.5)	0
Learning rate	(1e-3, 1e-2, 1e-1)	1e-3
epoch	(300, 400, 500)	500

XGBoost

Hyper parameter	Combination	**Best combination**
max_depth	(6, 7, 8, 9)	7
n_estimators	(800,900,1000)	1000
gamma	(0.5, 0.7, 0.9)	0.5
Learning rate	(1e-3, 1e-2, 1e-1)	1e-3

ARIMA

Hyper parameter	**Best combination**
p	2
d	1
q	1

7. Comparative RMSE

Comparative table with each models

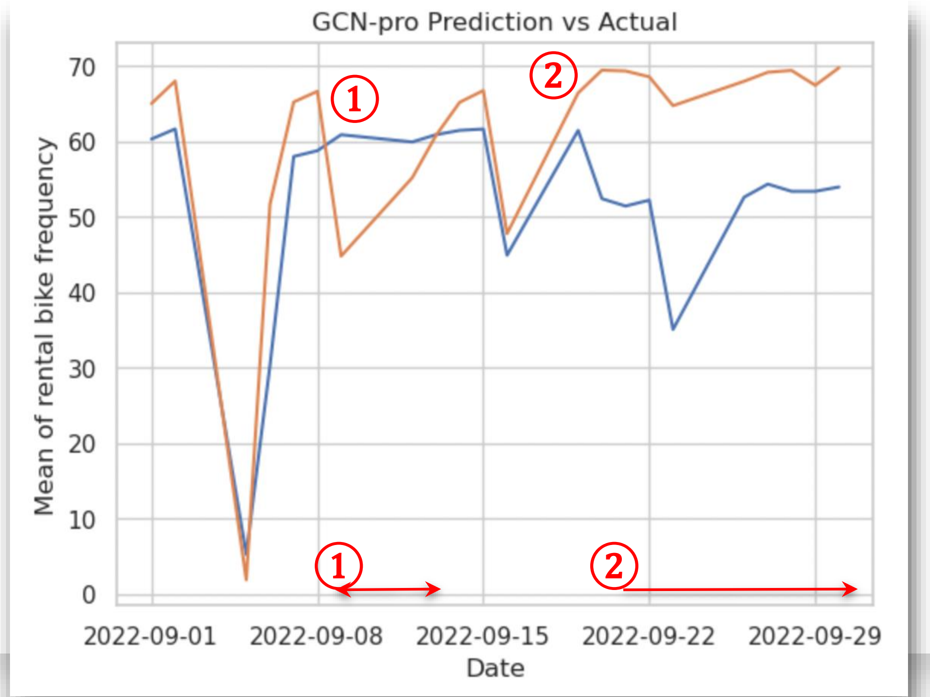
Model	GCN-pro	GCN-up	CNN	LSTM	XGBoost	ARIMA
RMSE	14.65	23.35	18.98	23.3	24.5	31.7

03

Result Analysis

Performance Analysis
Spatial Feature Analysis
Result Analysis

GCN Performance Analysis



Orange: Prediction value
Blue : Actual value

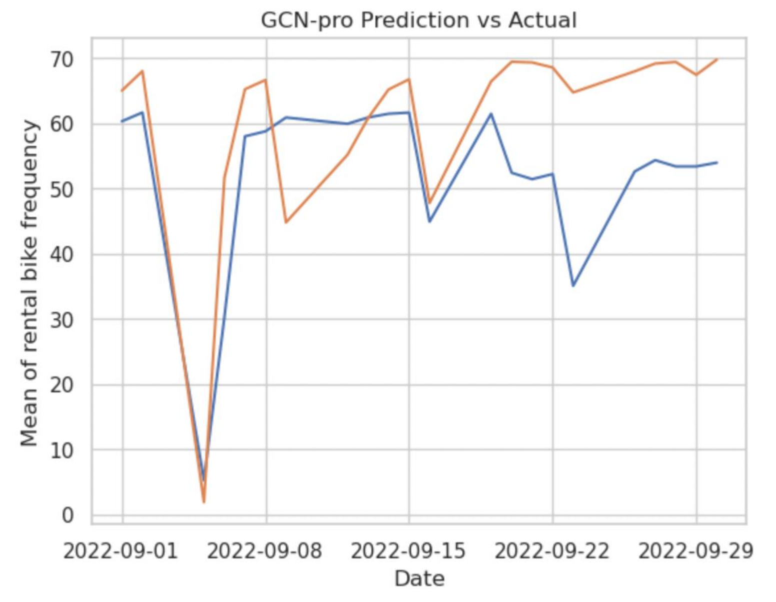
(1)
September 9-12 is an exception due to the Chuseok holiday

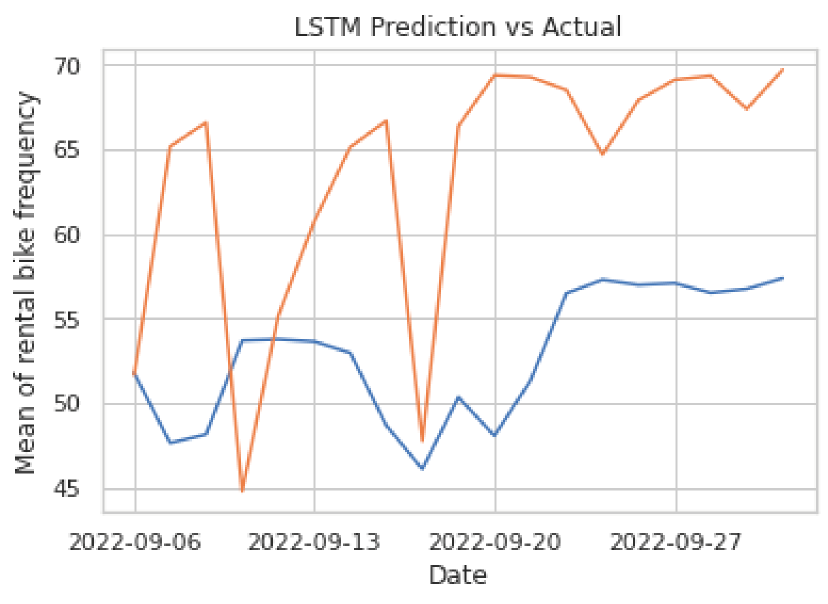
(2)
The model's performance declines after about three weeks from the initial prediction starting point of September 1st. This decrease in accuracy over time is a common issue observed in time series models.

GCN Performance Analysis

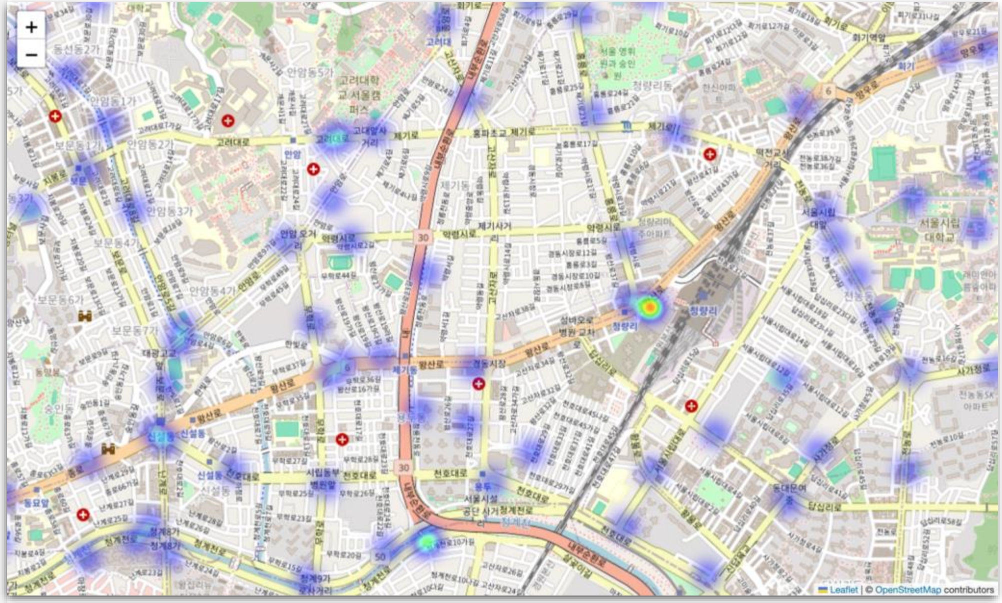
Comparative with LSTM

Orange: Prediction value
Blue : Actual value





Spatial Feature Analysis



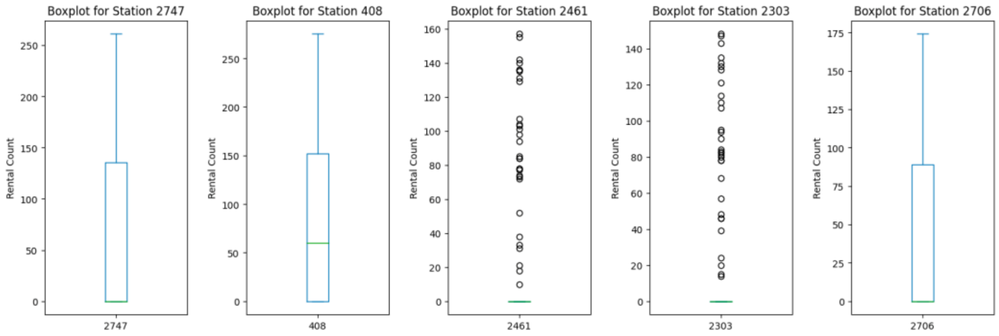
Heatmap of Seoul

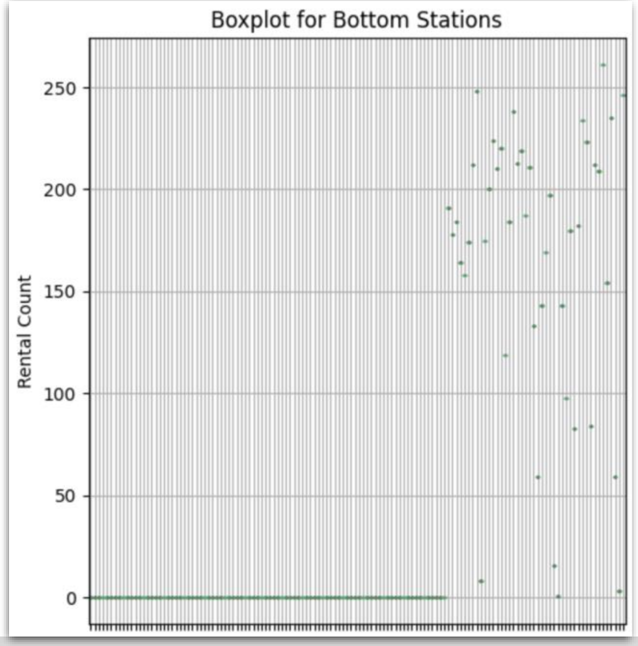
In most cases, the actual RMSE values are relatively small, however, due to the map's scale, they overlap and appear significantly larger.

Result Analysis

Worst case

Bicycle rental station with the **highest average RMSE** for September





04

Limitation

Limitation

1. Computational Cost
   - Colab Pro, University Research Account(Prof)

2. Rental stations built in the middle of 2022(2747 etc)

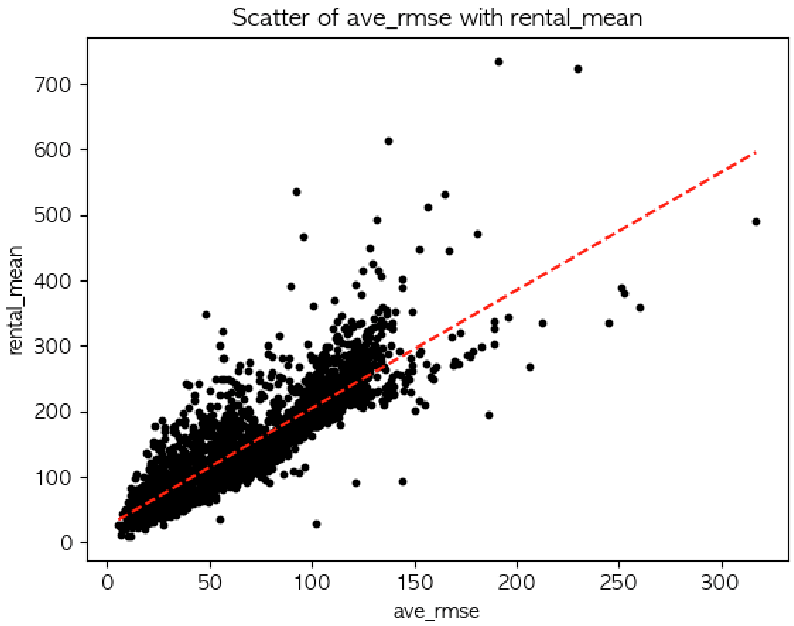
Limitation

4. Correlation score

Correlation score : 0.85
→ **The rental quantity and RMSE exhibit a high linear similarity**

⬇

We plan to contribute to the paper by addressing this issue through scaling the rental quantity and resolving the scale accordingly




```
Correlation score : 0.851017940050293
```

05

Outcomes

Outcomes

Korea Artificial Intelligence Association

Plos One(In Progress)

Predicting Bicycle Demand by Incorporating Station-Specific Spatial Features in a Graph Convolustion 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.

Keywords— *Bicycle Demand Prediction, Bicycle Rental Network, Graph Convolution Network, Spatial Feature Matrix*

I. INTRODUCTION

The burgeoning global interest in eco-friendly and healthy lifestyles has spurred a rise in demand for shared bicycle systems worldwide[8], highlighting the critical issue of supply-demand imbalances[10]. Traditional manual rebalancing methods, reliant on labor-intensive truck deployments, underscore the need for accurate demand prediction to mitigate these disparities. In Seoul, the rapid expansion of the public bicycle system, 'Ttareungi', without proper demand analysis, has led to increased user dissatisfaction due to supply-demand mismatches, necessitating precise demand forecasting for effective bicycle station placement and public bicycle distribution.

The complexity of predicting bicycle demand stems from the non-uniformity of rental and return locations, requiring consideration of the interconnectivity between stations, especially when forecasting across all of Seoul's rental stations. Additionally, spatial factors such as nearby bicycle paths, transportation facilities, and residential areas must be integrated with demand and weather variables to accurately influence rental volumes.

In our study, a graph-based model has been constructed where Seoul's bicycle stations are nodes connected by edges representing rental volumes, capturing the complex inter-station relationships. This model, a Graph Convolutional Network (GCN), integrates spatial and temporal data, including weather conditions, into its input matrix for a holistic spatio-temporal analysis. Subsequently, a Fully Connected Network (FCN) leverages this integrated data to forecast daily rental demand with enhanced accuracy over traditional models.

In the realm of public bicycle demand prediction [5] have contributed significantly with their research on Graph Convolutional Neural Networks (GCNs). Their study introduced a framework that not only reflects various spatiotemporal characteristics but also considers the influence of global variables, demonstrating robustness against sudden environmental changes. Their model, particularly the GCN-UP variant, showed superior performance by emphasizing the impact of users' past usage patterns over mere geographical proximity. However, they acknowledged the limitation of their model to existing stations and highlighted the need for future research to extend the graph structure to new stations.

Building on the foundational work by Bruna et al[1] who first introduced the graph convolutional neural network concept in their spectral networks study, further developed this concept. They proposed a GCN framework tailored for hourly demand prediction of bike-sharing usage at the station level. Their innovative approach utilized two distinct graph structures, GCN–IDW and GCN–UP, to encapsulate different spatial properties and to benchmark performance against each other[9].

Additionally, the work of Defferrard et al. expanded

Literature review

- Zhu, R., Tao, Z., Li, Y., & Li, S. (2021). Automated graph learning via population based self-tuning GCN. *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. https://doi.org/10.1145/3404835.3463056
- Kim, T. S., Lee, W. K., & Sohn, S. Y. (2019). Graph convolutional network approach applied to predict hourly bicycle-sharing demands considering spatial, temporal, and global effects. *PLOS ONE*, *14*(9). https://doi.org/10.1371/journal.pone.0220782
- Ligman, Drew, "Improved Hyperparameter Tuning for Graph Learning with Warm-Start Configuration" (2021). *Computer Science and Engineering Senior Theses*. 197. https://scholarcommons.scu.edu/cseng_senior/197
- Schrouff, Jessica & Wohlfahrt, Kai & Marnette, Bruno & Atkinson, Liam. (2019). Inferring Javascript types using Graph Neural Networks.
- Chai, D., Wang, L., & Yang, Q. (2018). bicycle flow prediction with multi-graph convolutional networks. *Proceedings of the 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. https://doi.org/10.1145/3274895.3274896
- Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-temporal graph convolutional networks: A Deep Learning Framework for traffic forecasting. *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence*. https://doi.org/10.24963/ijcai.2018/505

Literature review

- V E, S., & Cho, Y. (2020). A rule-based model for Seoul bicycle sharing demand prediction using weather data. *European Journal of Remote Sensing*, *53*(sup1), 166–183. https://doi.org/10.1080/22797254.2020.1725789
- Xu, C., Ji, J., & Liu, P. (2018). The station-free sharing bicycle demand forecasting with a deep learning approach and large-scale datasets. *Transportation Research Part C: Emerging Technologies*, *95*, 47–60. https://doi.org/10.1016/j.trc.2018.07.013
- Wang, Y., Zhang, N., & Chen, X. (2021). A short-term residential load forecasting model based on LSTM recurrent neural network considering weather features. *Energies*, *14*(10), 2737. https://doi.org/10.3390/en14102737
- Shi, Y., Zhang, L., Lu, S., & Liu, Q. (2023). Short-term demand prediction of shared bicycles based on LSTM Network. *Electronics*, *12*(6), 1381. https://doi.org/10.3390/electronics12061381
- Wang, B., & Kim, I. (2018). Short-term prediction for bicycle-sharing service using machine learning. *Transportation Research Procedia*, *34*, 171–178. https://doi.org/10.1016/j.trpro.2018.11.029
- Ji, H. (2022). Predicting district-wise bike-sharing demand using machine learning and deep learning algorithm case study of Seoul (Ddareungi). *Tilburg University*.
- Ohrn, A. (2020). London Bike Ride Forecasting with Graph Convolutional Networks. *Towards Data Science*.

THANKS!

Do you have any questions?