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Graph Neural Network: Weather and Weekday Prediction with Mumbai's Bike Rental Service

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Abstract

In this study, the usage of Graph Neural Networks (GNN) for weather and day-by-day forecasting in Mumbai was introduced. The data was collected from one of the leading bike rental company operating and situated in Mumbai and metrological department forecasting weather of Mumbai. It has been found that bikes are least rented in the months of heavy rain. Bikes rental is common among youngsters. Our suggested models fared better in terms of cross-entropy loss and validation dataset accuracy than the baseline model.

Keywords: GNN, Bike rental, Mumbai's Rain

1. INTRODUCTION

Urban transport systems are vital to contemporary cities because they give people a means of movement while also having a big impact on the social, economic, and environmental aspects of the city. Biking is a mode of transportation that has gained popularity recently. Bicycle rental programs have proliferated in cities across the globe and have shown to be an effective means of encouraging sustainability and a better way of living. These services can also be seen as socio-economic data sources with potential uses in the disciplines of social network analysis and urban economics. They may offer insightful information on human activity in urbanised areas.

In parallel, other algorithms have been developed since the Graph Neural Network (GNN) became popular for graph representation learning, including the Graph Convolution Network (GCN) (Berg et al, 2017). GNN-based models have been used to a number of fields, including social network recommendation (Fan et al., 2019) and molecular property prediction (Wang et al, 2022), as they are free from the degree of the nodes for the neural network architecture and permutation-invariant. Among the noteworthy subjects of GNN-based model implementations has been demand forecast for bike rental and ride-sourcing services, as seen in Beijing (Lin et al, 2018) and New York (Ma et al, 2022). Graph prediction is currently poorly understood, though, as prior research has only looked at the node regression of bike utilisation per station and the edge regression of travel record counts. Furthermore, because the dataset is represented by a graph that shows the relationship between journey records rather than the spatial proximity, the GNN-based models in the earlier studies did not consider the geographical proximity of bike stations as nodes. One potential limitation may be the inability to depict the homophily of nearby geographic areas. within the GNN-based model's nodes. Finally, no research has been done on GNN-based prediction tasks on Mumbai's bike rental programs yet.

2. MATERIAL AND METHODS

2.1 Graph Neural Network

GNNs are typically NNs that operate on data representations in the form of graphs. Nodes are joined by edges to form a graph. Data are linked to nodes, and the relationships between the nodes are indicated by the edges. Convolution extends from the application of filters on the rigid structure of grids to abstract mathematical operators that take advantage of the connectivity of nodes in its computation by using graphs as the input data structure. In GNN the authors decided to use a single graph to depict each event. Every detected pulse is depicted as a node in the graph, encompassing the per-DOM data. We regard the interconnectedness of the nodes in the graphs to be spatial because each node is connected to its eight nearest neighbours based on the Euclidean distance. To put it briefly, GNN builds a graph and uses the Euclidean distance to group similar events together in order to guess a target. Graph nodes are frequently furnished with feature vectors and labels in data-related applications. The feature matrix is represented by a $\eta \times d$ matrix X, where the feature vector of node i is found in the i-th row. To represent the label matrix, we use a $\eta \times c$ matrix Y, where c is the number of categories. For all nodes i, when they fall under category j. Y's rows are referred to as "one-hot" vectors. When there are just two categories, it is simple to describe the $\eta \times 2$ matrix Y equivalently using a $\eta \times 1$ binary vector called y.

2.2 Graph Convolutional Network

On graph-structured data, a Graph Convolutional Network, or GCN, is a semi-supervised learning method. It's based on a convolutional neural network variation that performs well and works directly on graphs. A localised first-order approximation of spectral graph convolutions serves as the motivation for the convolutional architecture selection. The model learns hidden layer representations that encode both local graph structure and node attributes, and it scales linearly in the number of graph edges.

The meteorological dataset derived from Ministry of Earth Science, Indian Metrological department (https://mausam.imd.gov.in/mumbai/) for period of three months when it rain the most in the entire city(1-7-2023 to 30-9-2023) and the data derived from the bike rental company for the same duration has been combined .This might be regarded as an estimate of the weather in Mumbai. The variables of the data set are:

Table I Variables Desciption

Variables	Object
Date	Object
Location	object
MinTemp	Float64
MaxTemp	Float64
Rainfall	Float64

Evaporation	Float64
Sunshine	Float64
WindGustDir	object
WindSpeed9am	Float64
WindSpeed3pm	Float64
Temp9am	Float64
Temp3pm	Float64
RainToday	Object
RainTomorrow	object
Bikes Rented	object

In our study Let G = (V, E) be a graph of the bike rental service dataset in a graph representation, where V and E denotes the bike stations used as nodes and travel records as edges on the day and note that |V| and |E| stand for the number of nodes and edges of graph G, respectively. Given $A \in \mathbb{R}^{|V| \times |V|}$, $H(k) \in \mathbb{R}^{|V| \times d}$, $W(k) \in \mathbb{R}^{d \times d}$, and $B(k) \in \mathbb{R}^{|V| \times d}$ which denote adjacency matrix of G, node embeddings matrix of dimension d(k), and weight matrix and bias matrix at layer k, respectively, the node embeddings matrix at layer k + 1 as a result passing of a GNN model is written as follows:

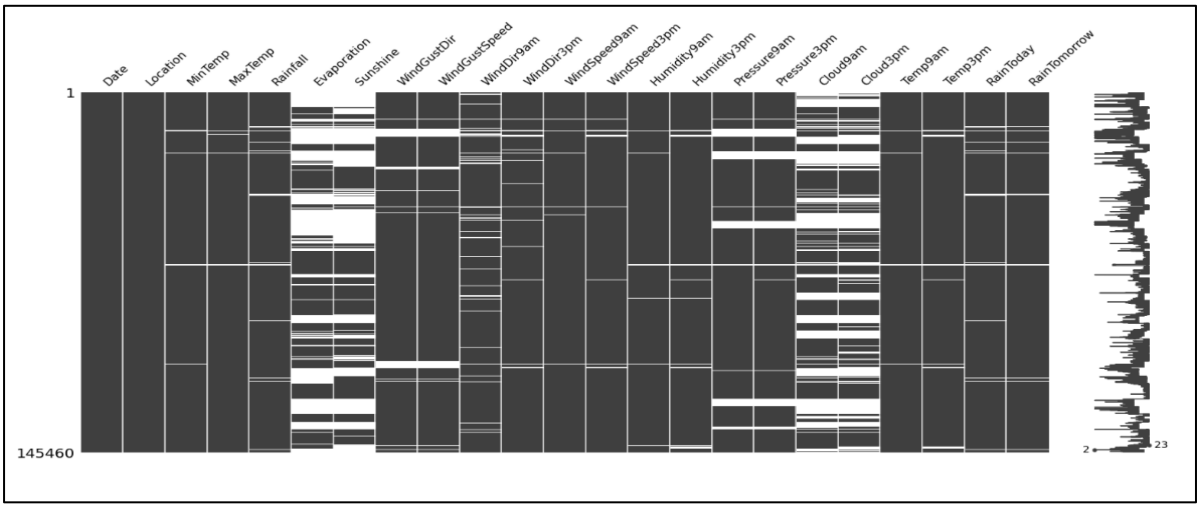
$$H(k+1) = \sigma\left((I + A)H(k)(W(k))^{\top} + B(k)\right),$$

3. DISCUSSION

Before starting further missing values are analysed using the command

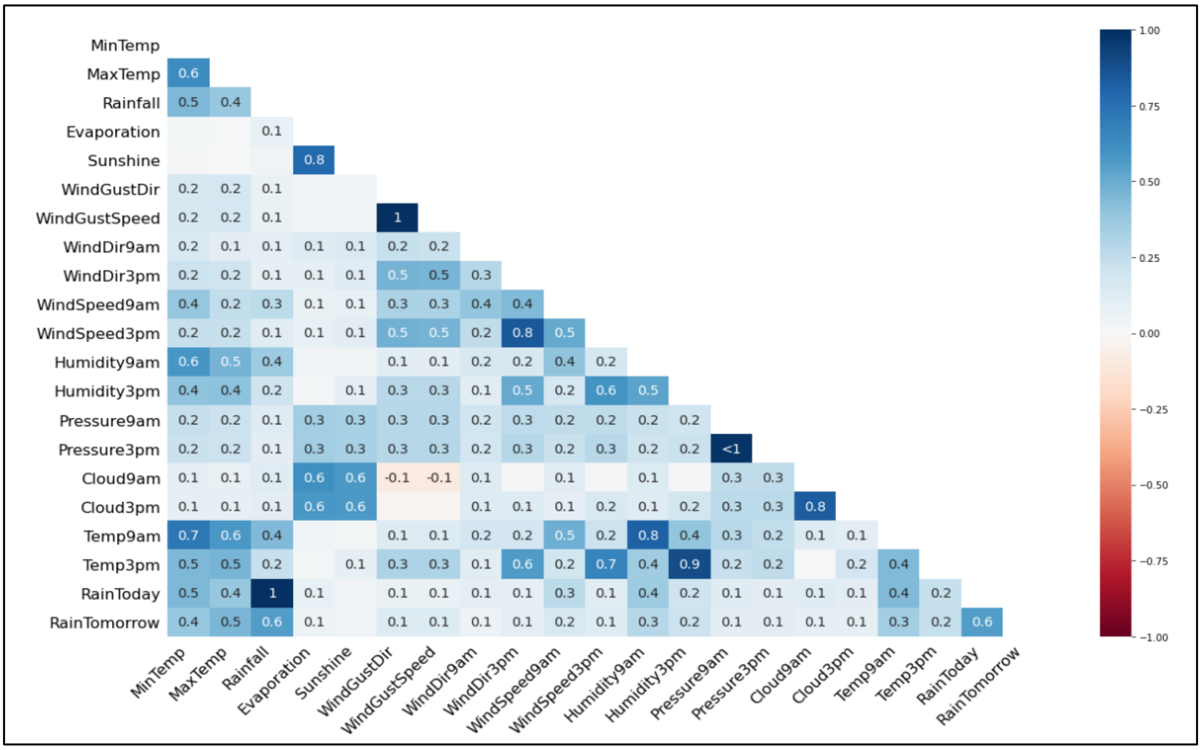
msno.matrix(rain)

Figure I Missing Value Analysis



The correlation heatmap was generated to evaluate correlation among the variables derived from the metrological department.

Figure II Correlation Matrix



This study evaluates 11 models in total. The base model, or Model 0, consists of two GNN layers (Berg et al, 2017), a global mean pooling layer as and two linear (or fully-connected) layers, with dropout layers (with probability p = 0.5) The mean, minimum, and maximum daily temperatures are likewise taken into account as input features by all other models.The prediction score was 81%.

Figure III AUC-1

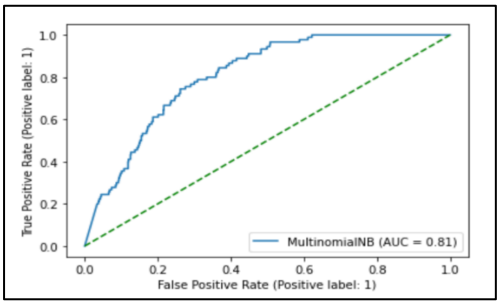
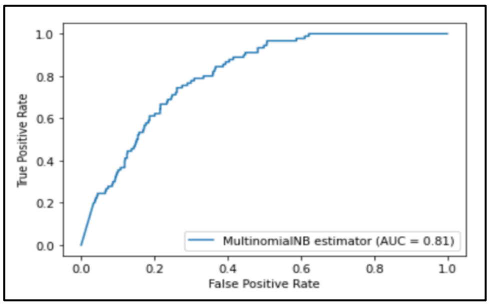


Figure IV AUC-2



4. CONCLUSION

In order to ascertain which model performs optimally for forecasting weather and day type based on bike rental demand, this study tested eleven different models. The model that used 5-nearest-neighbors to apply spatial graph coarsening during the training phase performed the best, as was to be expected. Nevertheless, the most accurate model could only achieve 81% accuracy.

We could have deployed a larger dataset with greater resources, which would have improved training and accuracy. Additionally, we took into consideration a cross-product of day type and weather type for the sake of prediction simplicity. For the multi-label classification challenge, we could have generated numerous categories using a combined loss function if we had had a sufficient amount of data. Additionally, the meteorological data taken into account was a rough estimate of Mumbai's weather. We could have divided the travel records into more precise time and geographic units if a more detailed dataset—such as hourly weather conditions broken down by district—had been available.

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