Graph Convolution Network approach for an efficient Bike Sharing System

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Abstract

Due to the low cost and flexible nature of Bike Sharing System there has been a significant increase of user in a short period. But the increasing popularity has also given rise to issues, affecting both users and bike operators. The key problem among which is the unequal distribution of bikes which is caused by fluctuating usage. Thus, efficient rebalance methods are required to effectively manage the requirements of bike at each station. In this research, I propose a framework based on Graph Convolution Network (GCN) which utilises DublinBikes historic data to predict the requirement of bikes at each station. To make the model accustom to climatic changes and its impact on the BSS weather features are also included as input parameters. The framework's performance is evaluated on root mean squared error (RMSE) and average Pearson Correlation (APC). The output obtained would aid bike operators plan efficient station network and can also be utilised for expansion of the network.

1 Introduction

Many metropolitan cities are currently facing a common road congestion issue that is partly responsible for increasing air pollution and causes psychological problems. To address such issues and build an eco-friendly environment the Bike Sharing System (BSS) is introduced. BSS provides the users with a convenient transportation alternative to travel short distances. A user can take a bike from any docking station near their starting point by swiping the travel card and can return the bike to any docks at their destination. Image of a docking station is presented in figure 1. While BSS has gained much popularity since its introduction and has established a broad user base, a major issue affecting the users has also gradually surfaced in the system.

Figure 1: Docking station in BSS.

With the increase in customer, the demand for bikes has proportionally risen but the availability of bikes at station vary greatly and depends on factors like location of the station, time of the day, day of the week and weather conditions. And for a successful BSS it is highly essential that it meets the demands of bikes at each station. Accordingly, there should be enough docks at stations to allow users to rest their bikes at their destination. And indeed, the most user complaints received are related to either shortage of bikes or unavailability of docks at stations.

Till date, many attempts have been made to resolve the bike rebalance issue but only a few researches that efficiently utilises the temporal (time varying) and spatial features of BSS data have been put forward. In majority of the work only one feature (temporal or spatial) is utilised to build demand prediction model due to relative complexity on managing both the features. Earlier works also suggested the use of cluster-based approach and obtained fairly good results but the only drawback was the difficulty in identifying individual stations among the clusters. Therefore, the need for an efficient system that can represent the requirements of the individual station and provide an ideal fix to the issue of rebalancing persists.

In this research, I propose a framework based on Graph Convolution Network (GCN) method to effectively address the issue of demands in DublinBikes (Dublin based bike sharing system). It utilises the property of graph that reflects dependencies between two nodes, and simultaneously incorporates both spatial and temporal features along with weather feature. The output obtained of the models would accurately predict the demands of bikes of at each station and accordingly measures can be taken. The key contributions of this research are mentioned below:

- This is the first research which utilises GCN based framework on DublinBikes data, to the best of my knowledge.
- Three-phase framework has been proposed for predicting demands of DublinBikes on each station. By experimentation ideal parameters to build GCN model and Fully Connected Neural Network (FCNN) model are determined.

The paper is further structured as: Section 2 reviews the related work in the field of BSS, Section 3 describes the proposed methodology, Section 4 presents the design architecture, Section 5 provide details of the proposed implementation methods, Section 6 reviews the selected evaluation metrics, Section 7 presents the proposed project plan and finally, Section 8 concludes the work.

2 Related Work

With the growing popularity of BSS many operational challenges started to emerge in running the system. Apart from the operational cost and maintenance issues the key problem of BSS is to relocate bikes from one station to another, to maintain the balance of bikes among stations (rebalancing issue) (Médard de Chardon, Caruso and Thomas, 2016). Also, for a steady operation of the system it is highly essential that factors affecting it are weighed effectively. In most of the previous works historic data of bike sharing schemes in New York, Seattle, Chicago and China is utilized to analyse the variation in ridership. Apart from analysing the spatial characteristics of data that represents the usage patterns many works also analysed weather conditions of that regions to identify the reason behind such patterns (Fishman, Washington, Haworth and Watson, 2015) (Gebhart and Noland, 2014). Few works also highlighted the relation between other modes of transportation (taxi) and BSS (Shaheen, Zhang, Martin and Guzman, 2011). By effectively incorporating these factors many solutions have been suggested that attempted to improve the shortcomings and aimed at solving the issues in the BSS. In this section a detailed review of approaches followed to solve the rebalancing issue and predict the demands of bikes at station level is provided. It also gives the reason for selecting the GNN methodology for this research with support from previous works.

2.1 Linear programming approach

Currently fleet of trucks are being used to rebalance the bikes among stations. But the high operational cost and manual labour included in process demands for an optimal solution. First in line methods focussed on optimizing the route for trucks so that at issue is resolved at minimum time. Many works treat the issue as an optimization problem and approaches in two ways: relocating bikes during day (dynamic rebalancing) and during night (static rebalancing). The work proposed by (Rajiv, Tzur and Forma, 2013) focused on optimising the routes of the trucks to rebalance stations overnight. They suggested an equation which helped determine the optimal paths for the truck by minimising the operating cost. They considered many parameters like how many bikes needs to be relocated, the distance between the stations, time taken to cover the distance and a penalty function. The penalty function represented the shortages of bikes at a station during the day and the procedure to calculate was suggested by (Raviv and Kolka, 2013). Although the proposed Mixed Integer Problem (MIP) model suggested optimal routes for vehicle (trucks), but the constraints applied made the practical application for the system of reasonable size quite unrealistic.

The Clustered MIP model proposed by (Schuijbroek, Hampshire and van Hoeve, 2017) outperformed the constraint programming approach. They suggested that clusters should be determined the system, the stations within which are self-sufficient for rebalancing. The formulated MIP model achieved fast computational performance and was suggested to be suitable for practical implementation, but it mainly focussed on static rebalancing. These papers like most of the earlier researches approached the issue individually focussing on one aspect and were identical to the traditional inventory management and routing problem. However, (O’Mahony and Shmoys, 2015) tackled rebalancing the stations during both day and night. Their take on the issue was somewhat different, instead of rebalancing they focussed on identifying the stations that are highly used for lenting and docking the bikes. They analysed the data of NYC CitiBike and found repetitive patterns in usage which assisted the cluster-based approach. The results of analysis were incorporated in determining the constraints for the optimization equation and eventually solve the rebalancing issue.

Although their solution for mid-day balancing has already been incorporated in CitiBike system it still leaves a lot of room for improvement.

2.2 Bikes demand forecasting model

Gradually the emphasis on determining the best routes for trucks to solve the rebalancing problem shifted to designing an efficient network of stations which considers the bike traffic at each station and accordingly allocate bikes to stations. To do so, researchers utilised machine learning and deep learning concepts to build prediction models. Many works tackle the BSS data with one of the two approaches: prediction and clustering. Prediction approaches basically tends to find the demand of bikes at station while clustering approach divides the stations into clusters based on mobility patterns of data.

Following the prediction approach, (Singhvi *et al.*, 2015) proposed a model that can accurately predict demands of bike among stations. They claimed that their model can be utilised to plan future expansion of station network. In their work, regression models were utilised with attributes like population, taxi usage and weather. NYC Citibike data was used for the research and focus was only given to the morning 7:00 am – 11:00 am duration. Model was tested on two scenarios: rainy weekdays and rainy weekdays. And their tests concluded that instead of targeting stations individually by taking pairwise trip data the models performance improved substantially. But this approach deviates the objective of predicting demand at individual stations, thus researchers suggested the use complex machine learning models over regression models.

(Yin, Lee and Wong, 2014) incorporated complex machine learning models like ridge regression, support vector regression, random forest and gradient boosted tree to predict the total counts of bikes required by the system by analysing the historic data of Washington DC bike scheme. They used root mean squared logarithmic error (RMSLE) as their evaluation parameter and concluded that random forest model achieved comparatively lower RMSLE (0.31) than other models. (Yang *et al.*, 2016) also used RMSLE as an evaluation parameter to measure the performance of random forest model they build to predict bike check-out at stations. And since they integrated their prediction model along with mobility modelling (cluster modelling) the efficiency of the model was much better than earlier models. But down the line, the neural networks models which efficiently handles the large-scale data were experimented with to achieve better prediction results (Xu, Ye, Li and Xu, 2018). (Pan, Zheng, Zhang and Yao, 2019) proposed the use of Long Short-Term Memory (LSTM) recurrent neural network model and evaluated its performance on RMSE. The LSTM model achieve an average RMSE value of 2.7069 and the results of calculating the net demand of bikes were almost accurate. The performance of LSTM model has also been suggested to outperform other neural network models and ARIMA models (Xu, Ji and Liu, 2018).

On the contrary, the cluster approach focuses on identifying the seasonal, weekly and hourly patterns based on the historic usage data. Particularly clusters approach is followed to understand the spatiotemporal properties in the data. (Zhou, 2015) formed five clusters depending on the demand density and time of use as shown in figure 2. And evaluated each cluster individually with different attributes and determined the clusters which are responsible for maximum trips for a period of two years. (Feng, Affonso and Zolghadri, 2017) incorporated two clustering methods: K-Means clustering and Hierarchical clustering.

They intended to gain insights from inter station patterns to utilise it in controlling and redesigning the system.

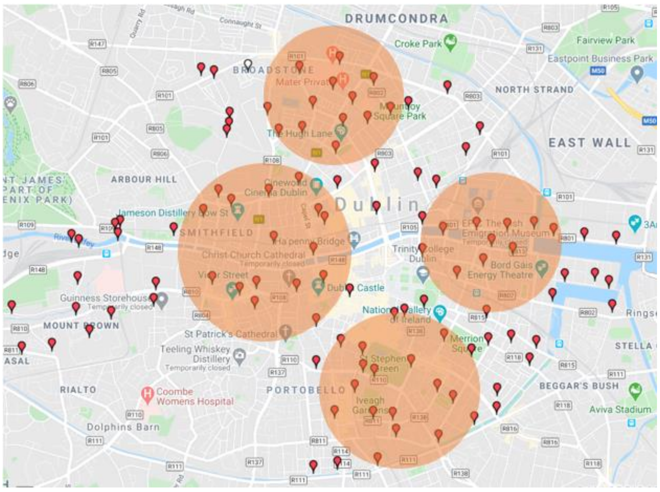

Figure 2: Demand density clusters in BSS.

2.3 Leveraging Graph structured data of Bike sharing system.

In general BSS is a network of stations which is connected by the movement of bikes. Hence it can be represented as a graph with stations as nodes and relationship between two stations (movement of bikes) as edges. (Scarselli *et al.*, 2009) introduced the GNN models to handle structured data. The traditional machine learning models required the graph data to be pre-processed into computable forms like vector, but by doing crucial node level features (location features) are often not captured. On the other hand, by directly feeding graph data into the model both the temporal and spatial properties are retained. (Chai, Wang and Yang, 2018) proposed their novel method of multi graph convolution network to utilise both temporal and spatial features of the graph data. Their model constituted of 3 stages: graph generation, graph convolution and LSTM encoder- decoder. They generated three different graphs based on distance, interaction and correlation between stations. These were fused and convolution was performed to obtain a convoluted graph. LSTM encoder-decoder was used to encode temporal patterns and the output was then passed to the FCNN. When experimented against other models like ARIMA, SARIMA, GBRT and LSTM their model achieved lowest RMSE values.

(Kim *et al.*, 2019) also exploited the graph data in their Graph Convolution Network (GCN) model. They generated three temporal graphs on hourly, daily and weekly features and extracted features of each graph using GCN models. The extracted features were then concatenated and passed to the FCNN as input along with attributes like weather. Low value of MSE and Average Pearson Correlation (APC) indicated better performance of the proposed model over other machine learning models.

After assessing the works that has been presented to resolve the issue of imbalance in BSS, I have been inspired to utilise a GCN based framework. (Chai *et al.*, 2018) and (Kim *et al.*, 2019) in both their research incorporated graph structure data was generated which simultaneously encodes the spatial and temporal features, and extract features. Few researches have also highlighted including global parameters like taxi usage (Singhvi *et al.*,

2015) and climatic condition (Fishman *et al.*, 2015). Thus, weather feature has also been included for training the model. For evaluation process majority of the researches use RMSE as an evaluation metric to determine relative prediction accuracy of the model. Also, a few recent researches also included APC as a metric to calculate relative variation between actual and prediction.

3 Research Methodology

3.1 Data gathering and pre-processing

In this research, I applied my model to historic data (January 2016 – December 2017) provided from the Dublin Bike Sharing System, "DublinBikes". The dataset is formed by combining Dublin Bikes Station data and DublinBikes user data. The DublinBikes station data is obtained from Smart Dublin Open source portal and DublinBikes user data is obtained from DublinBikes dynamic API. Table 1 provide details on the variables they contain. The station data contains information of 102 station and the user data consist of over 5 million user trips record, ranging from January 2017 to December 2019. Weather, as a global variable has also been included in this research, whose data is obtained from open weather API.

Datasets	Variables Count	Variables
DublinBikes Station	4	station number, station name, latitude and longitude.
DublinBikes User	6	Start trip timestamp, start trip station name, start trip location, end trip station name, end trip timestamp and end trip location.

Table 2: Summary of datasets

To utilise the dataset in the model first it is necessary to serialize the data into hourly demands. Since our data consist of 12 months duration, therefore total 8640 hourly demands are prepared for each station. Normalization is performed to standardize demands per station. Then 70 % of these hourly demands are used for training the model while the rest is kept for testing the model. Graph structured data is generated by using the feature matrix $\mathbf{H} \in \mathbf{R}^{N_s \times N_w}$ (Kim *et al.*, 2019), where N_s represents 102 stations and N_W represents temporal windows (hourly, daily and weekly) for each model.

3.2 Methods Applied

For this research, I've adapted Graph Convolutional Network (GCN) based framework for DublinBikes. GCN is a neural network architecture that operates on graph structured data (nodes and edges) and leverages the dependencies between nodes (stations) (Kipf and Welling, 2016). Before employing GCN the data must first be converted into graphs. The equation $\mathbf{G = (V, E, x_n)}$ generally symbolizes a graph where V represents the N number of stations, E denotes the edges between stations and x_n is the matrix of nodes feature (Kim *et al.*, 2019). For computing, the graphs are expressed in the form of adjacency matrix (A) and feature matrix (H). In this work, I composed adjacency matrix A considering the distance

between the station and three feature matrixes H with hourly, daily and weekly temporal windows.
At each layer the feature matrix H is multiplied with adjacency matrix A, this process transcribes the relationship between stations into features at each station. The output of this layer is again multiplied with adjacency matrix A, thus creating a chain of connections between stations and repeatedly transcribing relationship features at each station. The final output of the neural network H^{l+1}, final feature vector is utilised to the predict station level demands. The propagation rule followed for the graph convolution network at each layer is given below (Kipf and Welling, 2016):

$$H^{(l+1)} = f(H^l, A) = \sigma(AH^l W^l)$$

where $H^{(l+1)}$ is the final feature matrix which is function dependent of previous layer feature matrix H^l and adjacency matrix A. In the equation σ denotes the activation function utilized in the process and W^l represents the weight matrix. To standardize the adjacency matrix A at each station Laplacian normalization process (Kipf and Welling, 2016), presented below:

$$f(H^l, A) = \sigma(D^{-1/2} A D^{-1/2} H^l W^l)$$

where D is the degree matrix of A.

4 Design Specification

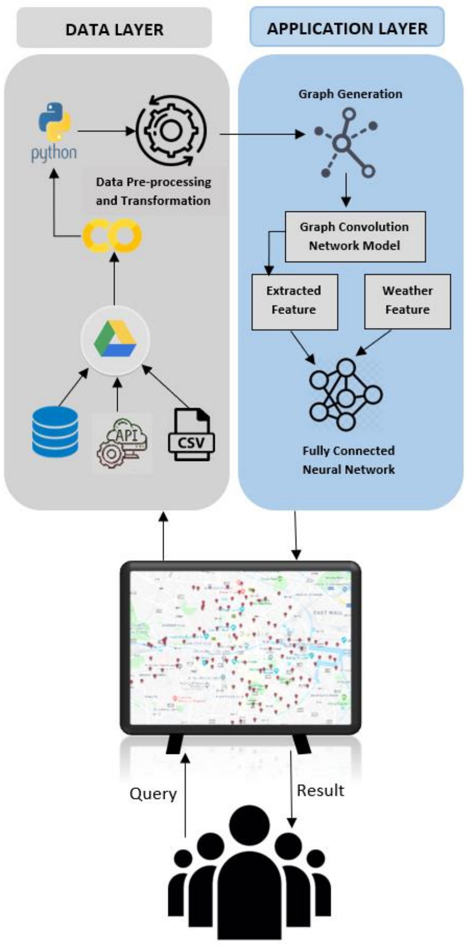

Figure 3 : Design architecture of bike demand prediction system.

The design architecture implemented for this research is presented in figure 3. It basically divides into two stage process; Data Layer and Application Layer. Data Layer comprises of data storage operations and Google Colab is used to access the the data stored in Google Drive. Since this research deal with matrix and large dataframes python libraries like pandas and numpy are quite used in preprocessing and transformation process. Application Layer represents how the transformed data is used to create graph to be used as an input for GCN model and how the obtained output is utilised along with weather feature to predict the requirement of bikes over a station.

5 Implementation

The framework proposed in this research is implemented in a three stages process; graph generation, feature fusion and FCNN as presented in figure 4.

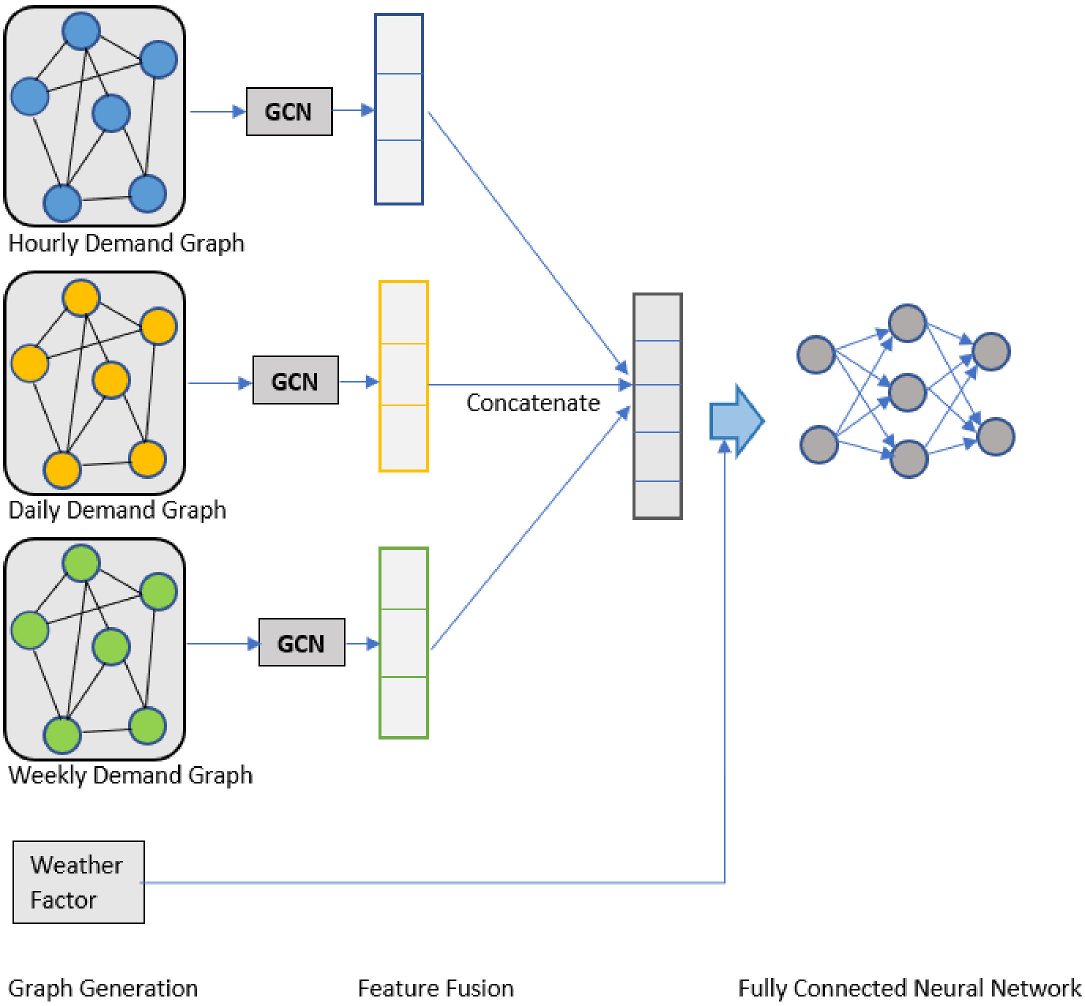

Figure 4 : Framework of Bike Demand Prediction.

5.1 Graphs Generation and Convolution

Generating the graphs from unstructured data is the most important part of the process. The graph structure of the data is represented by the adjacency matrix in python. For this research the adjacency matrix is created by utilising the DublinBikes station data. And to include temporal features different time range is selected. Accordingly, three temporals graphs are generated utilising the temporal feature of the stations and spatial characteristics of adjacency matrix. The best set of temporal features for the temporal grid is obtained through repetitive trial and error process. The structured data is then used as input in the GCN (Kim *et al.*, 2016). The description of parameters selected for the GCN model are mentioned in the table below:

Parameters	**Constraint**
Activation Functions	ReLU / Softmax
Number of Nodes	16/32/64
Number of epochs	300 – 500 (step 20)
Hidden Layers	2 -5

Table 2 : Parameter description.

The output obtained from each GCN model produces feature containing the spatial and temporal properties of the data. The features obtained from the three graphs are then concatenated together to be passed into the FCNN.

5.2 Fully Connected Neural Network

The concatenated features along with weather features are passed as an input into the FCNN to predict station level demands of bikes. The FCNN employed in the framework consists of 2 hidden layers, an input layer and an output layer. The optimum number of nodes for the hidden layers are obtained after experimentation with different nodes size (8/16/32/64/128). The nodes in the output layer are equivalent to the number of Dublin bikes stations (102). ReLU and Softmax are utilised accordingly as activation functions between the layers. And ADAM is adapted for the optimization method with a learning rate of 0.001.

5.3 Experimental Setup

The hardware configuration and software specification requirements for this research is given below in Table and Table 2 respectively.

Processor	**Memory**	**Processing Speed**	**Graphic Card**
Intel Core i7 8^{th} Gen / GPU	1 TB Hard Disk and 512 GB SSD	1.80 GHz	2GB Nvidia GEFORCE

Table 3 : Hardware Configuration.

Storage	Software	Libaries
Google Drive	Google Colab and Python 3	Numpy, Pandas, PyTorch, TensorFlow, Keras and scipy

Table 4 : Software Specifications.

6 Evaluation

In most of the previous works that were directed towards predicting the demand of bikes in BSS (Singhvi *et al.*, 2015) (Pan *et al.*, 2019), Root Mean Squared Error (RMSE) was selected as their evaluation parameter to measure the performance of their model. RMSE is a measure of how much the predicted outcome deviates from the ideal outcome. Therefore, a small value of RMSE is always desired. In (Kim *et al.*, 2019) and (Chai *et al.*, 2018) RMSE has also been used as an evaluation metric to evaluate the graph models previously suggested.

RMSE is generally represented by the following equation:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Predicted - Actual)^2}$$

Along with RMSE in (Kim *et al.*, 2019) Average Pearson Correlation (APC) has also been used to compare the similarities in the distribution pattern of actual and predicted demands. Inspired by the results demonstrated in their work and the relative importance of APC in determining the linear relationship between actual demands and predicted demands it has been used for evaluating the model proposed in this research. In general APC specifies the extent till which two or more factors vary together and is represented as below:

$$APC = \frac{1}{N}\sum_{i=1}^{N}\frac{cov(\hat{y}_i, y_i)^2}{\sigma_{\hat{y}_i}\sigma_{y_i}}$$

Where N indicates the total station count and cov is the covariance function. $\hat{y}_i$ represents the predicted demands and y_i represents the actual demand at each station, and σ indicates the standard deviation.

7 Project Management

Gantt chart in figure 5 indicates the 91 days' time period (June 2020 – August 2020) over which the project implementation and report write-up is divided. Each task in both sections is associated with its previous tasks, therefore enough time is allotted to each task.

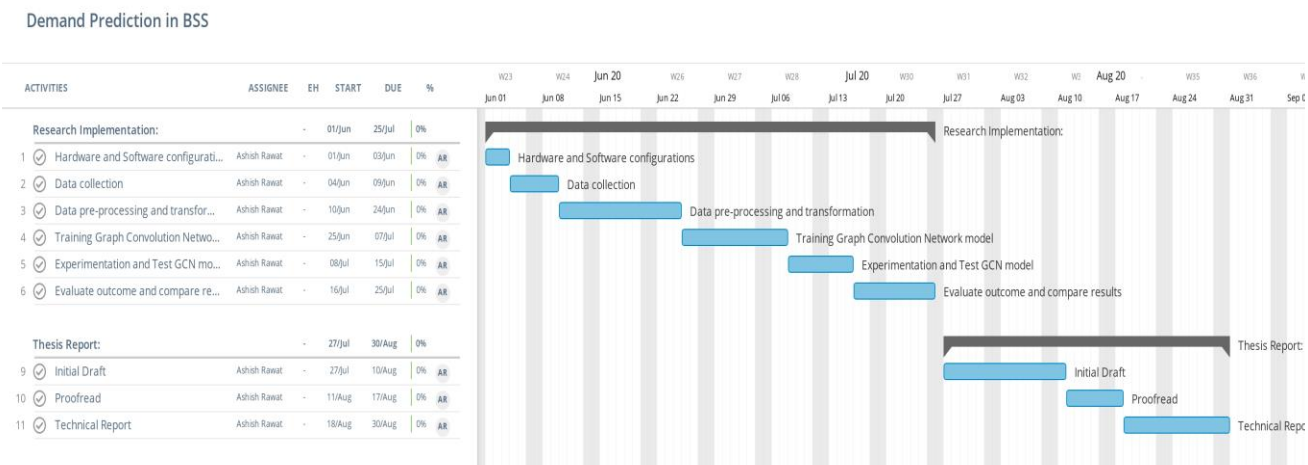

Figure 5 : GANTT Chart; Demand Preciction in BSS.

8 Conclusion and Future Work

This research proposed a framework that integrated GCN along with FCNN to predict the demands of DublinBikes at each station. By utilising GCN both the temporal and spatial features are simultaneously reflected in the convoluted feature. Further the affects weather features are included and passed as an input to FCNN along with the concatenated features. Hence, the predictive ability of the model is unaffected to variation in weather. Experimental results presented in previous works show the how the performance of previously suggested model that utilised GCN were far better than machine learning and deep learning models. Therefore, for the proposed framework I am expecting even better results. By predicting the demands at each station an efficient system can be planned and designed that is robust to demand traffic.

The proposed framework is susceptible to undefined stations in network, since it is trained on historic of data of the system. If real time updates of the system can be fed to the model at predefined period, then the model would be more robust to unforeseen stations. Additionally, if more features that directly or indirectly affects the BSS is include in training process the prediction accuracy of the model can significantly be improved.

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