GEOG 494 SP20 Research Project Report

Traffic prediction using Internet of Things sensors and deep learning

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Abstract: *Traffic prediction has been proved to be one of the scientific and efficient solutions to avoid congestion. The characteristics of complexity and nonlinearity of large-scale traffic data make the traditional prediction methods useless. This case study focuses on using the Internet of Things (IoT) and Spatio-Temporal Graph Convolutional Networks (STGCN), a Deep learning framework, to predict traffic speed in the New York City. Our experiment result shows that the STGCN can obtain both spatial and temporal feature for traffic data set, and it also have strong ability to carry out fast train with high prediction accuracy.*

Keywords: *IoT, Deep Learning, Traffic Prediction, STGCN*

1 Introduction and Background

1.1 IoT Definition

At present, modern technology involves almost every aspect of life, along with the vast popularization of the internet and wireless devices. The Internet of Things (IoT) has been introduced to represent a new form of communication between objects-objects and human-objects. The actual term "IoT" has been shown for only two decades. However, a similar concept can be traced back to the time of the invention of the radio and telecommunication. Until 1999, the "IoT" was named by Kevin Ashton. IoT builds the connection between objects, humans, times, locations, and devices so that all things can link as a web. It generally refers to as a things-connected network, in which things are connected wireless through sensors and often have ubiquitous intelligence (Xia et al., 2012). But there is no universal defined meaning for this term since IoT has been adopted by various groups, such as researchers, entrepreneurs, industrial employees, etc. A logical definition provided by McKinsey states that an IoT is sensors and actuators embedded in physical objects are linked through wired and wireless networks, often using the same Internet Protocol (IP) that connects the Internet (Chui, Löffler & Roberts, 2010). As the physical extension and virtual component of the internet, IoT shows the characteristics of collection, computation, communication, connection, and intellection. Sharply increasing population around the world and rapid urbanization development lead people's attention on how to organize themselves in a relatively small-framed region, such as in a city. IoT plays a more significant role in managing resources and fulfills the human's desire to live healthy, comfortable, and smart (Evans, 2011).

1.2 IoT Applications

The public may notice that the commonly used technological products have been experienced a "Smart" revolution. The concept of IoT has a leading role in this revolution. In 2013, the world already utilized about 5 billion "smart" connected things (Chase, 2013). The Business Insider projects that there will be more than 41 billion IoT devices by 2027 (Newman, 2020). When the connection between the world and the internet has become real, IoT has a tremendously broad reach and almost endless potential creation across different fields. The following aspects bring out some major IoT applications that transform how people live and work.

- Smart Home: IoT connects home appliances, security systems, and home energy equipment to an intelligent home network. It allows people to monitor and control their home devices and environment despite time and distance. (Malche & Maheshwary, 2017) For example, people can remotely open-air conditioner on the way back home; then, they can enjoy cool air at home right away. People also can set energy-saving temperature; once the inside temperature reaches that point, the air conditioner will automatedly shut down.
- Smart City: Due to the steep ascent trend of urbanization, it is a complicated situation to regulate since this takes along with economic, social, safety, and environmental issues. Smart city is a promising solution to improve the efficiency of infrastructure and services and protect the environment as well as set a sustainability plan for city development. Some cases include, but not limited to: a smart transportation system that helps traffic congestion problems and manages transportation rescores, like parking spots. Moreover, when air pollution monitor system become smart, it is able to effectively report and analyze air condition in the city and it can also help to create workable solution to control and reduce pollution issue.
- Smart Agriculture: Agriculture provides food products to support people's daily activities. IoT can help to solve many traditional farming issues, for example, drought management, yield optimization, land utilization, irrigation, and pest control, and it also can save resources and promote green framing. (Ayaz et al., 2019) Using IoT-based agriculture system to manage operations like fertilizing not only can precisely estimate the number of nutrients and increase production but also lower the risk of environmental problems that are caused by over-fertilizing.
- Smart Business: As humans and objects connect to the internet, smart business can support more general functionalities (Perera, 2018) and increase services and efficiency to create mature satisfactory conditions between both agent and client. One of the IoT wildly applied field is supply chain management. The packages will be marked by a unique ID, and then these IDs will be entered the internet. During delivery, the time and location will be updated on the internet. In this way, IoT supports real-time shipment tracking.
- Smart Health System: Since the sensor-embed devices allow detection and record real-time vital and other health data, a smart health system can build a well-organized database for individual patients. It will give huge benefits to medical decision-making and health monitoring. At the same time, IoT based smart hospital (Yu et al., 2012) presents an integrated hospital information system of diagnosis, treatment, management, and decision.

1.3 Graph Database

The development of the internet also innovates the way how to communicate, exchange information, and gain knowledge. As massive data generate from every day or even every second, people need to consider storage problems for such an enormous amount of data. The limitations of traditional databases, especially relationships, cannot be appropriately described, leading graphs, complicated structures, to store the data in a valid frame.

The most common representations of graphs are adjacency matrix and adjacency list, and the essential components of a graph are nodes and edges. In a graph data structure, nodes present entities, and each entity is related to different needs and applications; edges connect nodes, which is called a relationship. A relationship always consists of direction, from a start node to an end node, or a relationship can be two-way. A fundamental element of a graph database is that the importance of the information relies on the relations more heavily on the entities (Angles, 2012).

Graphs can represent lots of real-world scenarios. Both entities and relations contain properties (or attributes). In general, an attribute of node directly associates to an entity, and the name-value pair is a typical type of node attribute. Relations often carry quantitative properties, like weight, cost, distance, ratings, or time interval. Properties make the nodes and edges more descriptive and more suitable to fit into the real-life applications. (Pokorný, 2015) One of the daily life examples for the graph data structure is that it can represent a social network. Every person in the contact list is a node, and the attributes contain their information, like name and phone number. The relationship priority principle makes graph data models more expressive to network structure. As a “things, human, and internet” connected network infrastructure, IoT mainly adopts a graph database because graph modeling benefits IoT representations.

1.4 Background

The growing economy has also brought along with a better living standard for people. Besides public transportation, more people use vehicles to commute, and more families own cars. The American Driving Survey (Kim, Añorve & Tefft, 2019) published some statistics shows that each driver spent 51 minutes driving average 31.5 miles each day during 2016 and 2017. It also suggests that there is an increasing trend of driving. Free flow is essential for the transportation system. However, everyone travels through the city every day, and with more people involve driving, the trouble of traffic congestion is an ineligible situation in an urban area, which leaves several challenges for city planners and transportation departments. It causes perilous road conditions, impairs human health, and brings harmful pollution to the environment, such as air pollution and noise pollution. The new emerging concept of Smart Transportation System (or Intelligent Transportation System) has given solutions to this problem. Traffic prediction has been proved to be one of the scientific and efficient solutions to avoid congestion. The purpose of traffic prediction is to establish useful information for road users to optimizing routes and for the government to decrease congestion, reduce pollution, and improve traffic operation efficiency. Traffic prediction serves as a pivotal element for advanced traveler information systems, advanced traffic management systems, advanced public transportation systems, and commercial vehicle operation, when people gradually make headway in smart transportation (Lv et al., 2014).

2 Objective: Traffic Prediction

2.1 Traffic Congestion in New York City

NYC has a population of over 8 million residents, and it is the largest metropolitan area in the United States, with nearly 21 million people traveling through the city. The problem of traffic congestion in NYC is crucial. According to U.S. News ranking, NYC ranks Top 1 in the average 36.0 minutes commute times. NYC Department of Transportation (2019) has published an annual Mobility Report to analyzes trends and patterns of movements of city travelers. Travel demand is driven forward by the increasing number of residents, jobs, and visitors. The 2019 report contains taxi and For-Hire Vehicle (FHV: Uber, Lyft, etc.), and FHV sharply inclined with a 22.7% growth between 2016 and 2017. In Midtown, taxis, and FHVs represent almost 50% of the total traffic counted. Meanwhile, the report points out that travel speeds through Manhattan and across NYC have declined continuously since 2012, which results in more severe congestion, especially in the core area of Manhattan.

2.2 Relative Works

Traffic prediction is a crucial solution for congestion and also for building Smart Transportation System. Studies have introduced different methods for traffic prediction to improve traffic efficiency and transpiration management. The most commonly and traditionally used method is time series analysis since traffic flow has timestamps so that the data can be collected from a later time. Also, the complicated nonlinear data structure of traffic flow makes nonparametric methods stand out from the field. Recent decades, traffic data also consist of big data; the drawback of traditional data processing technique also push the trend of different machine learning algorithms. With the requirement of improving accuracy and meeting various traffic conditions, researchers have developed a hybrid model, which can adopt advantages from a combination of different techniques. Back to 1980, Levin and Tsao(1980) proposed Box-Jenkins time-series analyses to predict highway traffic flow, and they found that autoregressive integrated moving average (ARIMA) model was the most statistically significant for prediction at that time. Ding et al. (2002) used a support vector machine (SVM) in a timeseries model to predict traffic flow based on statistical learning theory. Still, the method limited the problem of local minimization and fast convergence in the predication. A short-term prediction model based on a new Bayesian Combination Method (BCM) was introduced by Wang et al. (2012). It can find the correlation between the historical traffic flow and real-time traffic conditions and quickly adjust components by detecting prediction errors, to obtain higher accuracy and stability compared with traditional BCM. Feng (2015) combined genetic algorithm and neural network with wavelet transformation and propagation neural network, which can optimize the network distribution and control weight value. This model can have better performance on both high frequency and low-frequency network analysis. The traffic flow data can also be deemed as the data has both characteristics of spatial and temporal features. By considering spatial features of a road network, which not only contains distance also average speed, Min and Wynter (2009) suggested a linear regression prediction model with spatio-temporal correlation with 5- minutes time period. Lv et al. (2014) applied a deep learning approach with considering the spatial and temporal process. They proposed a stacked autoencoder (SAE) model with a logistic regression prediction layer, and the results were shown that this approach has over 86% accuracy for both short-term and long-term prediction. Ma et al. (2015) recommended a model combined with Restricted Boltzmann Machine and Recurrent Neutral Network (RBM-RNN) architecture. This model is helpful in solving high-dimensional temporal sequence learning problems and predict spatiotemporal congestion pattern for large-scale transportation network congestion evolution. It can get as high as 88% of prediction accuracy based on deep learning theory.

3 Data

3.1 Data Description

Data Source:

New York City Department of Transportation. (2020). *Real-Time Traffic Speed Data* [Data file]. Retrieved from https://data.cityofnewyork.us/Transportation/Real-Time-Traffic-Speed-Data/qkm5-nuaq

NYC Real-Time Traffic Speed Data is collected by the Traffic Management Center (TMC) of the New York City Department of Transportation (NYCDOT). It contains real-time traffic speed information from locations where NYCDOT has installed traffic speed detectors around the city and updated several times per minute. The sensors mostly located on main arterial routes and highways within the five boroughs (The Bronx, Brooklyn, Manhattan, Queens, and Staten Island). Some important fields are displayed in Figure 1. They are ID, SPEED, DATE_AS_OF, and LINK_POINTS. IDs are link ID provided by TRANSCOM (Transportation Operations Coordinating Committee), and they represent different road segments in this data feed; SPEED is the average speed that vehicles passed endpoints on the link in the most recent time interval; DATE_AS_OF is the time that data received from the sensor links; LINK_POINTS is a combination of sequence of latitude and longitude coordinates, describes sensors' geographic location (Figure 2). Another two interesting fields are ENCODED_POLY_LINE and ENCODED_POLY_LINE_LVLS, which contains encoded link with speed station locations, and they can be decoded by Interactive Polyline Encoder Utility from Google Earth Platform (Figure 3).

ID	SPEED	TRAVEL_TIME	STATUS	DATA_AS_OF	LINK_ID	LINK_POINTS	ENCODED_POLY_LINE	ENCODED_POLY_LINE_LVLS
184	48.46	52	0	2020 Apr 20 09:24:10 AM	4616253	40.8347204,-73.86593 40.83357,-73.86199 40.8	_pfxF`}yaMdFsWfDmPpH}^lEgTBBBBB	BBBBB
423	56.54	94	0	2020 Apr 20 09:24:10 AM	4616299	40.7624804,-73.839391 40.76191,-73.839121 4	olxwFdwtaMpBu@jAg@\\\|@Yr@MdAGhA@dH\	BBBBBBBBBBBBBBBBBBBB
159	32.93	168	0	2020 Apr 20 09:24:10 AM	4616252	40.8563506,-73.87233 40.85219,-73.871371 40	ewjxF`e{aM~X_EfLs@pRFbE^fUlClPlC`TdE`Gb	BBBBBBBBBBBBB
223	41.63	63	0	2020 Apr 20 09:24:10 AM	4616341	40.70908,-73.9959 40.70895,-73.996941 40.708	w~mwFjisbMXnEXdCh@bCf@zAd@jA^r@	BBBBBBB
154	34.17	119	0	2020 Apr 20 09:24:10 AM	4616229	40.6757405,-74.00126 40.6765204,-74.0018 40	kngwFzjtbM{CjBilzG}Ap@yBXeACuA[uBw@uD	BBBBBBBBBBBBBBBB
426	52.81	129	0	2020 Apr 20 09:24:10 AM	4616272	40.7024204,-73.816481 40.700841,-73.815751	culwF~gpaMzHqCjUaKlGgDnl@wXndA_b@bR	BBBBBBB
259	42.87	94	0	2020 Apr 20 09:24:10 AM	4616223	40.6756,-74.841 40.67643,-74.001241 40.6772	omgwFfhtbMeDnAaDbB_F\\\|CqDzC_ARwAQqB	BBBBBBBBBBBBBBBB

Figure 1: The overview of the data feed. The important fields are ID, SPEED, DATE_AS_OF, and LINK_POINTS.

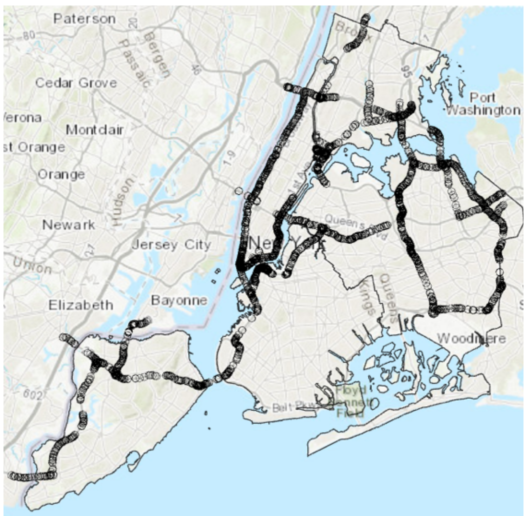

Figure 2: The map of LINK_POINTS, which shows sensors' geographic location

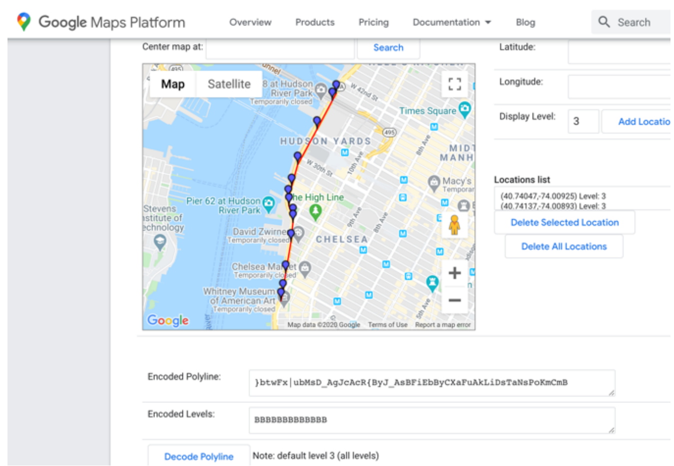

Figure 3: How to decode polyline using Interactive Polyline Encoder Utility from Google Earth Platform

3.2 Data Prepossessing

We abstract data of December 2019 and set the standard time interval to 5 minutes. After regrouping speed data by different ID and list by time from December 1st to December 31st, there are 139 IDs in the new speed dataset. We consider each link segment as a node in the road graph, so each link has 8928-speed records in December. The speed data is standard normalized, and the linear interpolation method is applied to complete missing value. After omitting two links that have all "0" speed records, the speed dataset size is 8298 × 137. The size of the weighted adjacency matrix is 137 × 137. The weighted adjacency matrix of the road graph in the traffic network is calculated by the distances between average sensors locations on the link. The mathematical formula for the distance between two links is

$$w_{ij} = \begin{cases} \exp\left(-\frac{d^2{}_{ij}}{10}\right), & i \neq j \text{ and } \exp\left(-\frac{d^2{}_{ij}}{10}\right) \geq 0.5 \\ 0, & else. \end{cases}$$

, where 10 and 0.5 are thresholds to control the distribution of the matrix to make sure that we do not assign weight when two links are close to each other.

4 Spatio-Temporal Graph Convolutional Networks (STGCN)

4.1 Graph Convolutional Network

Since classic CNN is not able to apply beyond standard grid data, convolution and filtering on graph data structure were involved by GCN. A graph has its unique ability to carry out the relationship within the dataset to represent many real-world problems. The primary purpose of GCN is to collect spatial features from a graph, and the idea is to generate a node through the aggregation of its features and surrounding neighbor features. There are two main research directions of GCN based on the type of how convolutions are operating; one is defined in the spatial domain; the other is defined in the spectral domain. Spatial graph convolution can be applied to the classic CNN approach by vertex filtering of aggregations of a signal into a certain grid format. Spectral graph convolution is based on the graph Fourier transform. Similar with fundamental Fourier transform, graph Fourier transform defines operate Laplacian matrix and its eigenvector on the graph and operate them at a particular frequency. In this way, spectral graph convolution can be computed by taking the inverse Fourier transform of the multiplication between two Fourier transformed graph signals. (Zhang et al., 2019)

4.2 STGCN in Traffic Prediction

Traffic prediction is a typical spatial and temporal process. Road networks are in the structure of networks, the prediction is sequential, locations are adjacent, and time and locations are dynamically dependent. Timeseries analysis used in early-stage is not suitable for stochastic and nonlinear large-scale high-dimensional data. Later, as computer science and other scientific fields make headway on AI, machine learning techniques have helped to handle big and complicated data. Deep learning, one of the primary machine learning methods, primarily adopted in the application of transportation systems. To sufficiently convert spatial information, researchers have used a convolutional neural network (CNN) to achieve extracting spatial features to correlate adjacency in road networks. However, traditional CNN mainly relies on the assumption of Euclidean structure, which graph, or video data has the same distance between each other. Since CNN cannot handle non-Euclidean structures, like traffic networks, researchers introduce graph convolutional networks (GCN). When CNNs can effectively process grid data, and GCN derives the correlation of graph data. Based on the Spectral Graph Theory and to better model the spatial and temporal relationships conformally, a novel deep learning framework for traffic prediction, STGCN, was introduced by Yin et al. (2018).

4.3 Network Architecture

The historical speed record is defined by Vt, which is a matrix composed of N sensor stations in M time intervals. The weighted adjacency matrix represents the distances between the sensor station. G is denoted for graph-based traffic data by Gt = (Vt, ε, W), where time step is t and ε is a set of edges that connect each station. The framework of the STGCN model composed of two spatio-temporal convolutional blocks and a fully connected layer (Yin et al., 2018).

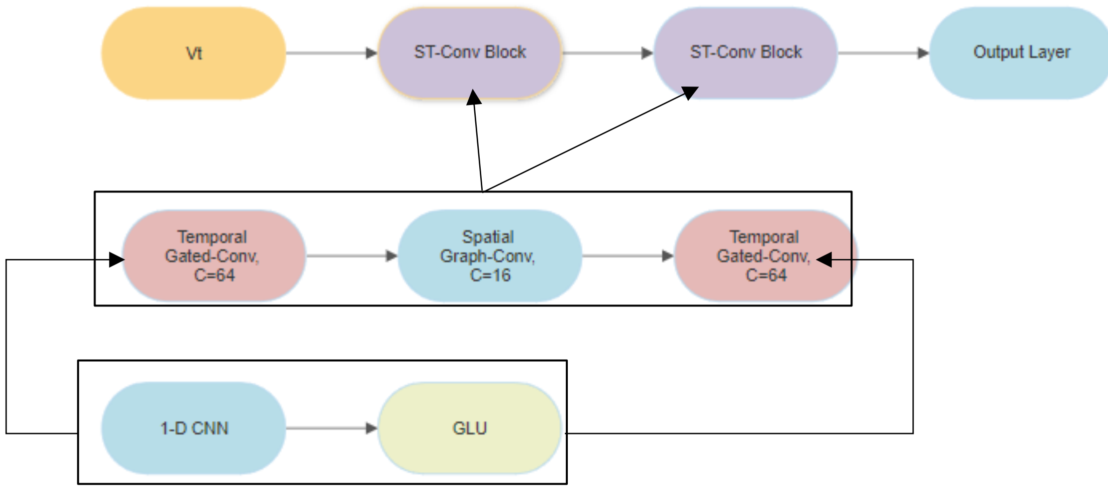

Figure 4: Architecture of STGCN. The input Vt was processed by two ST convolution blocks in order to keep spatial and temporal dimension along together. In each ST-Convolution block, there are two temporal gated convolution with filter size 64 and one spatial GCN with filter size 16. In each two temporal gated convolutions, there are graph CNN and gated linear unit (GLU) to maintain the nonlinearity of the model.

5 Experiment and Result

5.1 Experiment Setup

Computer configuration:

- Operating System: Windows 10 Home 64-bit
- System Model: GE62VR 6RF
- Processor: Intel(R) Core(TM) i7-6700HQ CPU @ 2.60GHz (8 CPUs), ~2.6GHz
- Memory: 16384MB RAM

Required interpreter:
The project model is running based on Python 3.7. The important library that used in the code are:

- SciPy 1.4.1
- NumPy 1.18.1
- Pandas 1.0.1
- TensorFlow 1.15.0

Code source:
Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. https://github.com/VeritasYin/STGCN_IJCAI-18
Experiment:
The test uses 60 minutes as a time interval to forecast both short-term and long-term speed. The speed data points are used to predict future speed in the 15, 30, and 45 minutes, so the time steps equal 3, 6, 9. The batch size is 50 and the Mean Absolute Errors (MAE), Mean Absolute Percentage Errors (MAPE) was calculated in order to model performance evaluation.

5.2 Evaluation Result

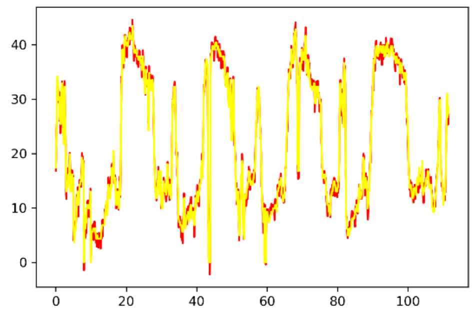

Figure 5: Speed prediction (miles/hr) in one day(24 hours). Each sub interval represent 4 hours.

Model	STGCN		
	MAPE (%)	MAE	RMSE
T=3 (15 mins)	3.192	3.865	6.685
T=6 (30 mins)	4.055	5.117	8.334
T=9 (45 mins)	4.739	6.021	9.621

Table 1: The STGCN model performance on the NYC real time speed data in December 2019.

The Figure 5 shows the visualization of STGCN model for traffic prediction. The yellow line represents the testing result and red line represents the actual speed record. For more directly to view the model accuracy, the table of STGCN performance on the NYC December 2019 dataset provide the value for mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE), which measures how well the STGCN model can give prediction for future traffic based on the real-time speed. The spatio-temporal blocks with Spatial GCN and temporal gated control convolution have filter size 16 and 64 respectively, which can maximize the effeteness of capture the spatial structure. These blocks also help to reducing model testing time and lessening parameter setting. The data size used to implement STGCN model is a middle size data, and the model test time is 52.629 seconds. With the output layer composed by another temporal gated control convolution, the corresponding temporal and spatial structure will merge together; meanwhile, the final prediction result will be exported by the last convolution layer. These processes can keep spatio-temporal correlation through the whole model in the greatest extent. Moreover, since the intractable dilemma of nonlinear and stochastic issue in traffic data, the model still has better performance for the short-term prediction than mid to long-term forecasting.

5.3 Implications

While we visualize our prediction plot on the map of LINK_PONITS (see Figure 2) through ArcGIS Pro, there is no specific cluster of stations that have higher prediction accuracy. There are only few stations locate in Manhattan have relatively higher accuracy, and these station are geographically located within one of the cluster of stations. However, the other stations does not have clearly spatial pattern with accuracy. From previous observation, we may assume that the station, which locate in the cluster may have higher accuracy for speed prediction. That is to say there exists an expectation for high prediction accuracy for the speed station, if this station is located around other stations. Therefore, our assumption of higher density of station will increase the prediction accuracy may need further investigation.

6 Conclusion

In this project, we implement the STGCN, one of the deep learning frame on the IoT speed sensors to predict speed in the New York City. The highlight of STGCN is its two spatio-temporal convolutional blocks that are consisted GCN and temporal gated convolution. This model shows the strong ability to coherently process spatial and temporal feature dependence, which provide efficient solution for speed forecasting in the Smart Transportation System. Based on our middle size speed data, our experiment predict future speed for next 15, 30, and 45 minutes respectively, the STGCN provide smaller MAPE, MAE, and RMSE values, and less training time. Since the model still have relatively lower accuracy for mid-long term traffic prediction, we will further optimize the model in order to solve this problem. Furthermore, we believe STGCN is a promising model to apply in IoT fields, since IoT require both spatial and temporal relationship. We will explore STGCN with another IoT data, for example like irrigation in smart agriculture.

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