PAN3

FYT Proposal

Spatiotemporal Fuel Consumption Forecasting

by

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PAN3

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1 Introduction

1.1 Overview

Eco-driving

Road transportation accounts for a vast amount of oil resources consumption and contributes nearly 80% in air pollutant emission in 2015, which in turn, impact climate change [1]. Eco-driving arises as a promising method to improve energy conservation and reduce as much as 25% overall vehicle fuel consumption and carbon dioxide emissions [2]. It is a modern and efficient way that emphasizes fuel efficiency through optimized road network, traffic conditions, and driving behaviors. To drive ecologically, drivers are encouraged to plan and consolidate their trips, maintain a steady driving speed, and anticipate traffic flow to avoid congestion, which in combination, increases the fuel economy [3].

Fuel consumption forecasting

Regional and road-based fuel consumption forecasting that takes into account of the road distance, speed, and traffic features are crucial to assist drivers in choosing most fuel-efficient routes to their destination. In this project, we will be utilizing a big dataset of private cars in China that contains trips and trajectories of dozens of thousands of cars. Each car trip contains information about the fuel consumption level, speed, location, and other features.

1.2 Objectives

The goal of this project is to predict the regional and road-based fuel consumption level at the next period, driving time + T, given historical fuel consumption, speed, and trajectory data.

To achieve our goal, we will mainly focus on the following objectives:

1. **Design and implement a novel temporal graph neural network (T-GNN) framework** to investigate how cars flow through a network of roads with varying fuel consumption level. Graph neural networks (GNNs) [4] can model the network dynamics and information propagation, while temporal graph neural network (T-GNN) can further incorporate the temporal dependency in time series data.
2. **Develop baseline models** – both statistical and deep learning-based methods. Our novel framework should outperform the baseline models.
3. **Create visualization** to effectively present the recommended route to our end users.

The biggest challenges we expect to face will be to transfer cross-domain knowledge and techniques to our problem, as to our best knowledge, this is the first work to model fuel consumption forecasting problem using heterogeneous data.

1.3 Literature Survey

Existing work on spatiotemporal forecasting has been focusing on the canonical traffic prediction and ride-hailing demand forecasting tasks, but the techniques are also transferable for the fuel consumption forecasting problem. We study and exploit the predictive power of different GNN architecture under an end-to-end learning framework. In particular, we listed some of the state-of-the-art models below:

1.3.1 Spatiotemporal Multi-graph Convolution Network (ST-MGCN)

ST-MGCN [5] improves the spatial dependency modeling capability of previous work using *multi-graph convolution*. The multi-graph incorporates polymorphic relationships between regions. For temporal dependency modeling, the paper introduces *contextual gated recurrent neural network* (CGRNN) to reweight different historical observations through a contextual-aware gating mechanism.

1.3.2 Diffusion Convolutional Recurrent Neural Network (DCRNN)

DCRNN [6] integrates *diffusion convolution* – a bidirectional random walk on graph with sequence-to-sequence learning framework to model spatial dependency and non-linear temporal dynamics. To mitigate the discrepancy between the training and testing distributions, the work leverages *scheduled sampling* [7] technique to gradually change the input distribution using probability decay.

1.3.3 Deep Multi-View Spatial-Temporal Network (DMVST-Net)

In addition to LSTM and local CNN that encode complex sequential interactions and spatial relations, DMVST-Net [8] proposes the usage of *graph embedding*, as a semantic view to model correlations among regions sharing similar temporal patterns. Such representation is later transformed into feature vectors using a flatten layer and are used as context features in a fully connected model for final prediction.

1.3.4 Temporal Graph Convolutional Network (T-GCN)

T-GCN [9] captures the topological structure of urban road network and dynamic change of traffic over time by combining graph neural network (GNN) and gated recurrent unit (GRU). Multiple convolutional layers are stacked together to incorporate multi-hop dependencies via neighborhood aggregation scheme.

2 Methodology

2.1 Design

To capture the spatial and temporal dependencies in the fuel consumption forecasting task, we propose a novel framework – *Multi-graph Diffusion Convolutional Network* (MG-DCN), which harness the power of multi-graph [5] and diffusion convolution [6] in a joint model.

2.1.1 Model Overview

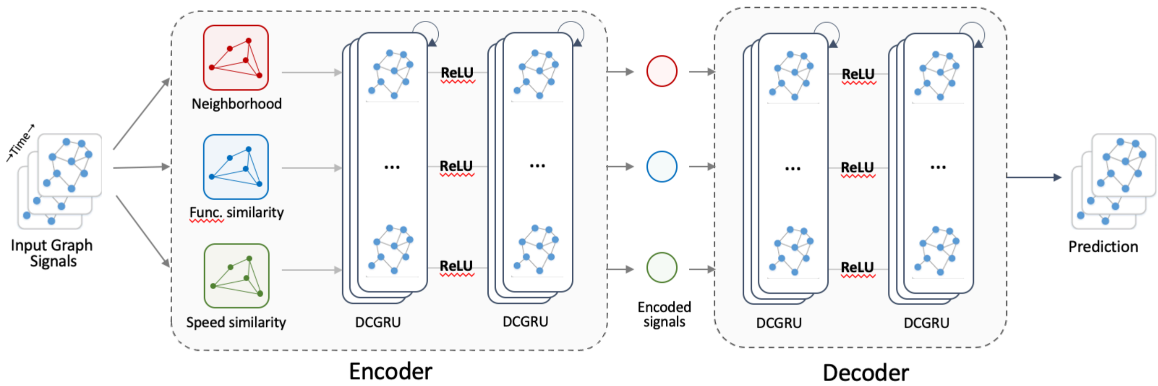

Figure 1. Architecture of Multi-graph Diffusion Convolutional Network (MG-DCN).

We feed the preprocessed time-dependent fuel consumption data extracted from our big dataset of private cars to the MG-DCN model as graph signals. The model learns non-Euclidean correlations of spatial dependency using multi-graph, captures temporal dependency by leveraging diffusion convolutional gated recurrent unit (DCGRU) [6] cell, and makes long-term prediction using the Seq2Seq architecture [10].

2.1.2 Multi-graph

In order to choose the most efficient route, we have to consider the combinational impact of route distance, road speed, and traffic behavior on the fuel consumption pattern. Therefore, we propose three weighted graphs to model different semantics of pairwise relationships between road segments: (1) *Neighborhood* graph $\mathcal{G}_N = (V, A_N)$ to capture spatial proximity, (2) *Functional similarity* graph $\mathcal{G}_F = (V, A_F)$, and (3) *Speed* embedding $\mathcal{G}_S = (V, A_S)$ to encode semantic similarity and speed similarity between road segments. Among these, the neighborhood graph is a directed graph to represent the driving direction, while others are undirected graphs. This can be extended to model new types of correlations by constructing additional graphs.

Figure 2: An example of different correlations between road segments. To predict fuel consumption in region 1, spatially adjacent region 2, functionally similar region 5, road speed correlated region 4 are considered.

2.1.3 Supersegment

Intuitively, different sections of a road can possess very distinctive traffic and speed behavior. To capture the fine-grained fuel consumption behavior at different locations, we define nodes in the multi-graph as road segments, in which each road segment holds unique spatial, functional and speed features. With this, we turn the non-planar urban road network into a planar graph without any edge crossing. In this work, we refer to the complete set of road segments as *supersegment* [11].

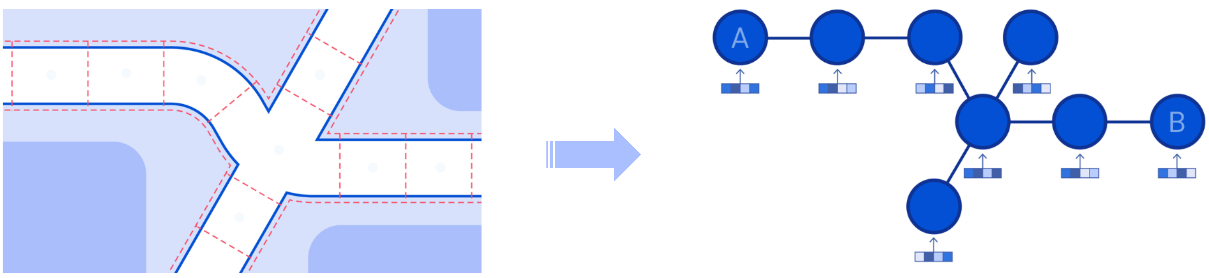

Figure 3: Urban road network is divided into road segments (represented as nodes in multi-graph) according to their combinational feature of spatial proximity, functionality and road speed.

2.1.4 Seq2Seq Architecture

Route recommendation requires multi-step ahead forecasting to generate sequence of road segments as the final prediction. Therefore, we employ *Sequence-to-Sequence* architecture [10] to process and encode input sequence data to a fixed-length of representation as the final state of the encoder. Based on the encoded state, the decoder then generates predictions at various time steps.

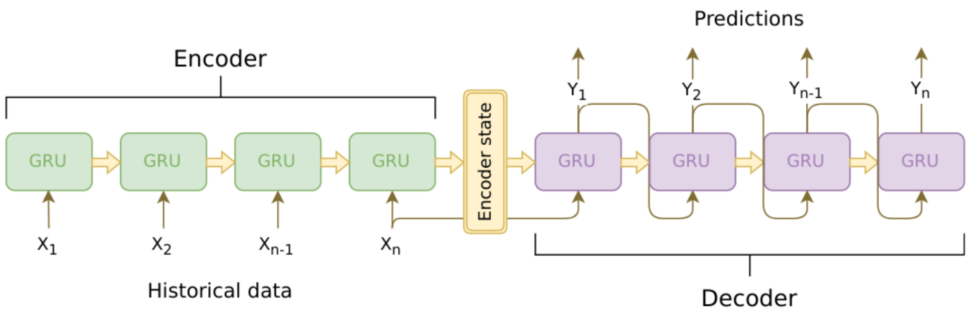

Figure 4: General Seq2Seq architecture with gated recurrent unit (GRU) cell.

In our work, GRU cell in the general encoder-decoder architecture, as shown in Figure 4, is replaced by *Diffusion Convolutional Gated Recurrent Unit* (DCGRU) cell to form the Recurrent Neural Networks (RNNs) in both encoder and decoder in our work. DCGRU addresses the limitation of the popular spectral graph convolution, i.e., ChebNet [12] which requires the graph to be undirected. Diffusion convolution serves as the generalized form of graph convolution and is defined on both directed and undirected graphs using a bidirectional graph random walk.

2.2 Implementation

The Implementation Phase will include the following aspects:

2.2.1 Dividing road network into supersegment

We will carry out data cleansing and data transformation as the preprocessing step to first extract necessary information (road speed, driving speed, fuel consumed, distance travelled, etc.) for the prediction task. Besides, we will obtain road-specific point of interests (POI) information and urban road network from external sources like OpenStreetMap, Baidu Maps, and Google Maps to construct the supersegment [11].

2.2.2 Multi-graph construction

Neighborhood graph captures the topological structure and spatial distance of supersegment in the road network. Its adjacency matrix is defined based on the connectivity of segments on the same road or connected through a junction/intersection:

$$A_{N,i,j} = \begin{cases} sim_N(v_i, v_j) & if\ v_i\ and\ v_j\ are\ on\ same\ road\ or\ connected \\ 0 & otherwise \end{cases} \tag{1}$$

where $v_i, v_j \epsilon \mathbb{R}$ are representation vectors of supersegment and sim_N is the Minkowski distance between two road segments on the urban road network. Minkowski distance is a generalization of both Euclidean and Manhattan metrics [13] and has shown to have better approximation power by computing distance similarity of vectors.

Functional Similarity graph connects nodes that share the same POI to model the influence of POI on traffic flow at different road segments. The adjacency matrix is defined as:

$$A_{F,i,j} = sim_F(P_{vi}, P_{vj}) \,\epsilon\, [0,1] \tag{2}$$

where $P_{vi}, P_{vj} \epsilon \mathbb{R}$ are the POI vectors of the road segment v_i and v_j respectively and

sim_N is the normalized Jaccard distance between two POI vectors.

Speed embedding is a fully connected graph in which weight of edges represents road speed similarity to provide semantics information of individual road segment. Its adjacency matrix is defined as:

$$A_{S,i,j} = DTW(S_{vi}, S_{vi}) \in [0, \infty) \tag{3}$$

where DTW is the dynamic time warping distance that measures similarity between two sequences and $S_{vi}, S_{vi} \in \mathbb{R}$ are speed vectors of supersegment in a 5-minute time interval.

2.2.3 Diffusion Convolutional Gated Recurrent Unit (DCGRU)

Diffusion Convolution The diffusion convolution operation over a graph signal $X \in \mathbb{R}^{N \times P}$ and a filter f_θ is defined as:

$$X_{:,p\star\mathcal{G}} f_\theta = \sum_{k=0}^{K-1} \left(\theta_{k,1} (D_O^{-1} W)^k + \theta_{k,2} (D_I^{-1} W^T)^k\right) X_{:,p} \quad for\, p \in \{1, \dots, P\} \tag{4}$$

where $\theta \in \mathbb{R}^{K \times 2}$ are parameters for the filter and $D_O^{-1} W, D_I^{-1} W^T$ represent the transmission matrices of the diffusion process and the reverse one, respectively.

As proposed in DCRNN, we replace the matrix multiplications in traditional GRU with diffusion convolution operation.

$$r^{(t)} = \sigma(\Theta_{r\star\mathcal{G}}\left[X^{(t)}, H^{(t-1)}\right] + \mathrm{b}_r) \tag{5}$$

$$u^{(t)} = \sigma(\Theta_{u\star\mathcal{G}}\left[X^{(t)}, H^{(t-1)}\right] + \mathrm{b}_u) \tag{6}$$

$$C^{(t)} = \tanh\,(\Theta_{C\star\mathcal{G}}\left[X^{(t)}, (r^{(t)} \odot H^{(t-1)}\right] + \mathrm{b}_c) \tag{7}$$

$$H^{(t)} = u^{(t)} \odot H^{(t-1)} + \left(1 - u^{(t)}\right) \odot C^{(t)} \tag{8}$$

where $X^{(t)}, H^{(t)}$ denote the input and output at time *t*, $r^{(t)}, u^{(t)}$ are reset gate and update gate at time *t*, respectively. $\Theta_r, \Theta_u, \Theta_C$ are parameters for the corresponding filters and $\star\,\mathcal{G}$ denotes the diffusion convolution operation defined in Equation 4.

2.3 Evaluation

Evaluation Metric

We will be using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to evaluate our model, which are defined as follow:

$$RMSE = \sqrt{\sum_{i=1}^{N} \left(\hat{y}_{t+1}^{i} - y_{t+1}^{i}\right)^2} \tag{9}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{\left|\hat{y}_{t+1}^{i} - y_{t+1}^{i}\right|}{y_{t+1}^{i}} \tag{10}$$

where $\hat{y}_{t+1}^{i}, y_{t+1}^{i}$ are the predicted value and ground truth of fuel consumption level for road segment *i*, at time *t+1*, and *N* as the total number of road segments.

Baseline Model

We will be comparing our model with both statistical and deep learning-based method: (1) *Shortest Travel Time*: rely on the assumption that the most fuel-efficient route has the shortest travel time, (2) *DCRNN*: one of the state-of-the-art deep learning models for traffic prediction. Our model is expected to outperform both baselines by incorporating temporal dependency and multiple spatial correlations in the fuel consumption pattern.

3 Project Planning

3.1 GANTT Chart

Task	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr
Study related work and conduct literature review								
Design the methodology – data preprocessing								
Design the methodology – graph construction								
Design the methodology – model architecture								
Design the experimental setup								
Analyze dataset provided								
Conduct data cleansing and preprocessing								
Present findings from exploratory analysis								
Transform data and develop supersegment								
Design baseline models								
Build the baseline model I – shortest travel time								
Build the baseline model II - DCRNN								
Conduct experiment on baseline models								
Analyze baseline results and present findings								
Refine novel framework – MG-DCN								
Construct multi-graph								
Develop main model – MG-DCN								
Conduct experiment on MG-DCN								
Conduct hyperparameter tuning on MG-DCN								
Optimize MG-DCN								
Analyze experiment results and present findings								
Create visualization for final results								
Code documentation and refactoring								
Write the proposal								
Write the monthly reports								
Write the progress report								
Prepare presentation slides and poster								

4 Required Hardware & Software

4.1 Hardware

Development PC:	PC with MS Windows 10 or later
Minimum Display Resolution:	1024 * 768 with 16-bit color
Server PC:	PC with 1TB hard drive

4.2 Software

Python	Programming languages
PyTorch/Tensorflow Keras	Deep learning library

5 References

[1] Y. B. Cui, “Study of automobile emissions saving countermeasures,” *Science & Technology Vision*, vol. 4, p. 190, 2014.

[2] "Fuel-efficient driving techniques | Natural Resources Canada" https://www.nrcan.gc.ca/energy-efficiency/energy-efficiency-transportation/personal-vehicles/fuel-efficient-driving-techniques/21038. (accessed 9 Sept. 2020)

[3] "Fuel Efficient Driving Guide | The Simple Dollar" https://www.thesimpledollar.com/insurance/auto/fuel-efficient-driving-guide. (accessed 9 Sept. 2020)

[4] T. Kipf and M. Welling (2016), "Semi-Supervised Classification with Graph Convolutional Networks". Presented at ICLR 2017. [Online]. Available: https://arxiv.org/abs/1609.02907.

[5] X. Geng, and Y. Li et al., (2019), "Spatiotemporal Multi-Graph Convolution Network for Ride-hailing Demand Forecasting". Presented at AAAI 2019. [Online]. Available: http://www-scf.usc.edu/~yaguang/papers/aaai19_multi_graph_convolution.pdf.

[6] Y. Li, R. Yu, C. Shahabi, and Y. Liu (2018), "Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting", Presented at ICLR 2018. [Online]. Available: https://arxiv.org/abs/1707.01926.

[7] S. Bengio, O. Vinyals, N. Jaitly and N. Shazeer (2015), "Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks", *arXiv.org*, 2015. [Online]. Available: https://arxiv.org/abs/1506.03099.

[8] H. Yao et al. (2018), "Deep Multi-View Spatial-Temporal Network for Taxi Demand Prediction", *arXiv.org*, 2018. [Online]. Available: https://arxiv.org/abs/1802.08714

[9] L. Zhao et al. (2018), "T-GCN: A Temporal Graph Convolutional Network for Traffic

Prediction", *arXiv.org*, 2018. [Online]. Available: https://arxiv.org/abs/1811.05320.

[10] I. Sutskever, O. Vinyals, and Q. V. Le (2014), "Sequence to Sequence Learning with Neural Networks". Presented at NIPS 2014. [Online]. Available: https://papers.nips.cc/paper/5346-sequence-to-sequence-learning-with-neural-networks.pdf.

[11] "Traffic prediction with advanced Graph Neural Networks", *Deepmind*, 2020. [Online]. Available: https://deepmind.com/blog/article/traffic-prediction-with-advanced-graph-neural-networks.

[12] S. Tang, B. Li and H. Yu, "ChebNet: Efficient and Stable Constructions of Deep Neural Networks with Rectified Power Units using Chebyshev Approximations", *arXiv.org*, 2019. [Online]. Available: https://arxiv.org/abs/1911.05467.

[13] R. Shahid, S. Bertazzon, M. L Knudtson, and William A Ghali, "Comparison of distance measures in spatial analytical modeling for health service planning". *BMC Health Services Research*, 2009. [Online]. Available: https://bmchealthservres.biomedcentral.com/articles/10.1186/1472-6963-9-200

6 Appendix A: Meeting Minutes

6.1 Minutes of the 1st Project Meeting

Date: Sep 3, 2020
Time: 03:00 pm
Place: Zoom call
Present: Mr. Ahmad Alhilal, Dr. Tristan Braud, Zhi Yun
Absent: None
Recorder: Zhi Yun

1. Approval of minutes
   This was the first formal group meeting, so there were no minutes to approve.

2. Report on progress
   2.1 Zhi Yun has read the project abstract and suggested readings posted on the Final Year Project (FYP) website.
   2.2 Zhi Yun has researched on recent academic publications about spatiotemporal forecasting and Graph Neural Networks online.
   2.3 Zhi Yun has drafted the project plan: break down the work package into tasks, determine project dependencies, identify important milestone, and build a project management timeline.

3. Discussion items
   3.1 Mr. Ahmad introduced the project and the big dataset of private cars in China.
   3.2 Dr. Tristan and Mr. Ahmad suggested looking into more related work to design the novel framework
   3.3 The proposal should include methodology for data preprocessing, graph construction and basic experimental setup.
   3.4 Mr. Ahmad recommended having shortest travel time as the first baseline model.
   3.5 Mr. Ahmad mentioned that Zhi Yun is free to use any development tools available (Tensorflow, Pytorch, etc.)
   3.6 Mr. Ahmad showed the sample data and attributes of the big dataset and shared the previous publication of the team to give Zhi Yun a better understanding of the dataset.

4. Goals for the coming week
   4.1 Zhi Yun will review other relevant work on spatiotemporal forecasting

4.2 Zhi Yun will begin designing methodology for data preprocessing, T-GNN model and experimental setup

5. Meeting adjournment and next meeting

The meeting was adjourned at 04:00 pm.

A Skype group is set up to facilitate communication within the group.