CTFP: Cloud-Powered Road Traffic Forecasting and Route Planning for Connected Vehicles

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***Abstract*—Predicting the future urban traffic and planning better vehicle routes are important for various purposes. They are also challenging tasks since dynamic urban traffic affected by various spatial and temporal features is difficult to predict. Therefore, in this paper, we introduce a Cloud-powered joint framework of urban Traffic Forecasting and vehicle route Planning, called CTFP, based on spatio-temporal graph attention networks for connected vehicles.**

***Index Terms*—Traffic prediction, route planning, connected vehicles, spatio-temporal graph**

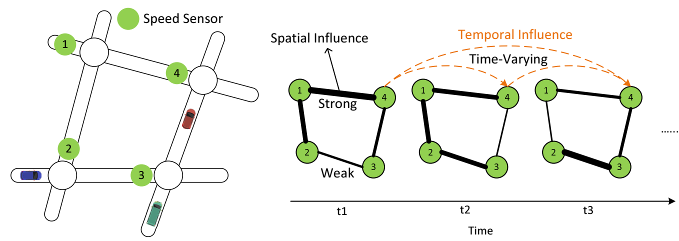

Fig. 1. Spatio-temporal features in a road network.

I. Introduction

Predicting future urban traffic and planning better vehicle routes are important for various purposes [1]. Meanwhile, they are also challenging tasks since dynamic urban traffic affected by various spatial and temporal features is difficult to predict. For the future intelligent transportation systems (ITS) with connected and automated vehicles (CAVs) [2], jointly modeling them becomes more challenging because the predictions and the planned routes are mutually influenced. As shown in Fig 1, several road sensors as speed sensors (e.g., loop detectors and cameras) are installed in an urban road network. From a spatial point of view, each speed sensor not only reflects its own traffic status, but also influences the speed readings of neighboring sensors. From a temporal point of view, speed readings in each sensor are time-varying caused by vehicle traffic.

Therefore, in this paper we introduce a Cloud-powered joint framework of urban Traffic Forecasting and vehicle route Planning, called CTFP, based on spatio-temporal graph attention networks for connected vehicles. The CTFP considers both local and global spatio-temporal relationships for a road network, which may improve the performance for mid- and long-term forecasting. We also suggest a feedback model for vehicle route planning based on the congestion contribution model [3].

The remainder of this paper is organized as follows. Section II introduces related work for urban road traffic prediction and route planning. Section III describes the design of the proposed architecture. Section IV concludes the paper along with future work.

II. Related Work

Benefiting from the advances of deep learning models, several significant advances have been made in the field. One representative model is the DCRNN [4] for urban traffic forecasting. More recent work has shown better performance by the attention mechanism, including HGCN [5], PM-MemNet [6], and ST-GAT [7]. For route planning and travel time estimation, several new models have also been proposed, such as SAINT+ [3] and FDNET [8].

Despite recent advances, several major limitations and challenges still remain:

- Unexpected anomaly incidents (i.e., vehicle accidents and temporary parking vehicles) in an urban area pose threats to forecasting and route planning.
- Considering the future CAVs, when detecting road congestion, vehicles may choose to reroute to detour the traffic. This kind of travel pattern can significantly reduce the reliability of current traffic forecasts.
- When rerouted vehicles alter the current traffic pattern, it is a challenging task to introduce a feedback mechanism to the current models, which can hardly receive feedback from a changed pattern.

To tackle these problems, we propose CTFP to better optimize route planning in urban areas.

III. Joint Framework of Urban Traffic Forecasting and Route Planning

The architecture of CTFP is shown in Fig. 2. A vehicle equipped with a communication module can upload its mobility information, such as location coordinates, speeds, and planned routes, toward a vehicle traffic cloud (VTC) via a base station, e.g., gNodeB. Meanwhile, various road infrastructures can also upload the road traffic statistical information to the VTC, such as average speeds of a road via loop detectors and throughput of a road. The VTC collects all this information to generate predictions for the future traffic through a traffic prediction engine (TPE). The generated predictions are inputted

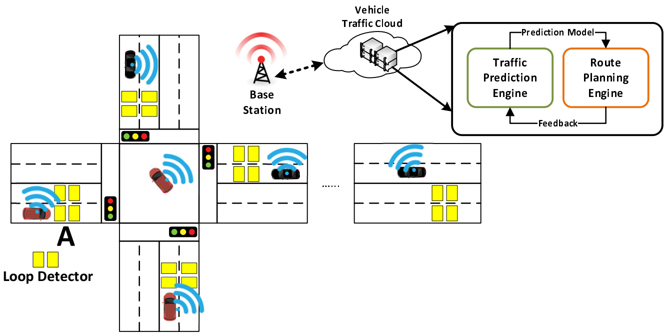

Fig. 2. The proposed cloud-powered urban traffic prediction and route planning architecture.

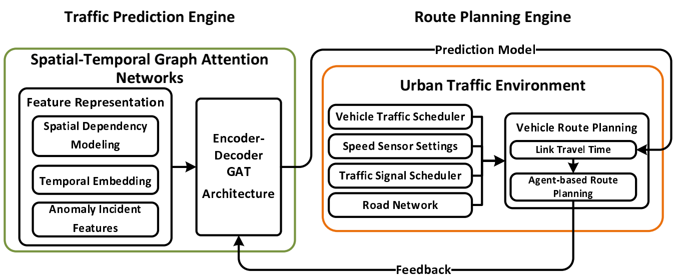

Fig. 3. The feedback model for vehicle route planning.

into a route planning engine (RPE) that recommends optimized path information for vehicles. We introduce the CTFP in detail as follows.

A. Spatial-Temporal Graph Attention Networks for Traffic Prediction

In a VTC, the TPE and RPE work together to provide an optimized urban route planning service to vehicles. The proposed TPE employs a spatial-temporal GAT (STGAT) network to generate urban traffic predictions. STGAT uses multiple feature representations such as spatial dependency modeling, temporal embeddings, and anomaly incident features to train the autoencoder network.

Fig. 4 shows a general GAT autoencoder network architecture. It uses spatial-temporal graph signals as input, which are generated from road speed data. This speed data include both spatial and temporal relationships, as shown in Fig. 1. The embeddings with a positional encoding are input for an encoder to train the model. The output of the encoder #1 can be connected to one or more encoders for multiple rounds of training. After training the encoders, the parameters K and V, are forwarded into the decoder modules that have the same dimensions as the encoder's. With the trained parameters, the decoders can receive an input having a sequence of road speed data for a duration to generate a future prediction.

B. Vehicle Route Planning

The prediction model from TPE can generate traffic forecasts in the near future. With this forecasting, the RPE can build a link travel time graph based on the congestion contribution model [3] to schedule new vehicle paths based on demands. An agent-based route planning will simulate current

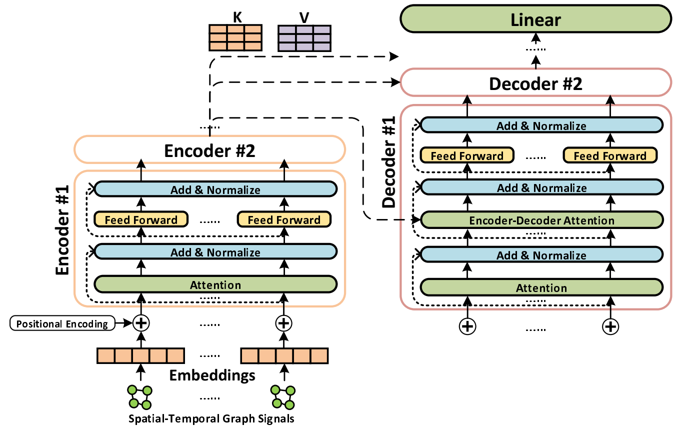

Fig. 4. An encoder-decoder graph attention networks architecture for urban traffic forecasting.

schedule paths based on the latest traffic prediction, which will serve as a feedback to TPE.

IV. Conclusions

In this work we have introduced a cloud-powered framework of road traffic forecasting and vehicle route planning for connected vehicles. For the future work, we will try to fine-tune the proposed framework to improve the performance of path planning.

Acknowledgments

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