1. **Spatio-temporal Graph Convolutional Network: A Deep Learning Framework for Traffic Forecasting-IJCAI 2018**

Due to the nonlinearity and complexity of traffic flow, traditional methods cannot satisfy the requirement of mid-and-long term prediction tasks and often neglect spatial and temporal dependencies.

Based on the length of prediction, traffic forecast is generally classified into short-term (5-30 mins) and long-term prediction (over 30 mins).

The methodologies on traffic prediction can be classified into two categories: dynamical modelling and data-driven methods.

Classic statistical and machine learning models are two major representatives of data-driven approaches. ARIMA-based models are limited by the stationary assumption of time sequences. Recently, classic statistical models have been vigorously challenged by machine learning methods of traffic prediction tasks.

Deep learning approaches:

To take full advantage of spatial features, some researchers use convolutional neural network (CNN) to capture adjacent relations among the traffic network, along with employing recurrent neural network (RNN).

Wu and Tan presented a feature-level fused architecture CLTFP for short-term forecast.

Afterwards, Shi et al. proposed the convolutional LSTM.

RNN-based networks are widely known to be difficult to train and computationally heavy.

Above all, we proposed a novel deep learning architecture, the spatio-temporal convolutional networks. This architecture comprises several spatio-temporal convolutional blocks, which are a combination of graph convolutional layers and convolutional sequence learning layers, to model spatial and temporal dependencies.

Experiments

To verify the model, two real-world datasets are selected, Beijing and California.

Beijing: There are 12 road segments in total, and the traffic data are aggregated every 5 minutes. Time period spans from 1st July to 31th August. The first historical data are selected as training set and the rest are used as validation and test set respectively.

California (PeMS): 1026 stations are used.

All the tests use 60 minutes as the historical time window (12 observations) to forecast traffic conditions in the next 15, 30, and 45 minutes.

Model comparison

HA, LASR, ARIMA, FNN, FC-LSTM, GCGRU

Metrics:

MAE, MAPE, RMSE, and Training Efficiency

1. **Multistep speed prediction on traffic networks: A deep learning approach considering spatio-temporal dependencies**

How to incorporate network topology into prediction paradigm?

Multistep prediction to obtain a relative long-term future traffic condition is more adapted to practical ITS applications.

This topic is challenging primarily due to the non-Euclidean topology structure of traffic networks, the stochastic of the time-varying traffic patterns, and inherent difficulty in multistep prediction.

Proposed a new model: Attention Graph Convolutional Seq2Seq model

More recently, deep learning models have been widely and successfully employed in computer science; meanwhile, it has drawn substantial attention in the transportation field…….However, the models with deep architectures above do not distinguish spatial variables across topological adjacency, which will definitely compromise the effects of capturing spatial correlations.

CNN models are restricted to processing Euclidean-structured data.

The graph convolutional network (GCN) was developed to generalize the convolution on non-Euclidean domains in the context of spectral graph theory (Kipf and Welling, 2016).

Related papers:

Diffusion convolutional recurrent neural network: Data-driven Traffic Forecasting-Y Li, R Yu, C Shahabi

High-order graph convolutional recurrent neural network: a deep learning framework for network-scale traffic learning and forecasting, Cui et al.

As a classic time-series prediction problem, the nearest m-step observation data can provide valuable information for multistep traffic speed forecasting. In addition to the real-time traffic speed information, some exogeneous variables such as the time-of-day, weekday-or-weekend, and historical statistic information (average, min, max, median historical speed at time I road j) are also helpful to predict the future traffic speed.

Problem formulation:

V^{~}\_{t+n}=argmax\_{V\_{t+n}} Pr(V\_{t+n}|V\_t,V\_{t-1},…,V\_{t-m;G}