# A Survey of Hybrid Deep Learning Methods for Traffic Flow Prediction


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## ABSTRACT

Traffic flow prediction using big data and deep learning attracts great attentions in recent years. Researchers show that DNN models can provide better traffic prediction accuracy than the traditional shallow models. Since the traffic flow reveals both spatial and temporal dependency characteristics, and may be impacted by weather, social event data etc., therefore, a set of hybrid DNN models have been presented recently in literature for further improving the traffic flow prediction performances. The hybrid models can capture dependency in multi-dimension and show better prediction performances than simple DNN models. This paper presents a thorough review and comparison of hybrid deep learning models for traffic flow prediction. We review the data sources used in hybrid deep learning and the various hybrid deep learning models built for traffic flow prediction. The benefits of using hybrid models are summarized.



## CCS Concepts

**•Networks** → *Network monitoring;*

## Keywords

Survey, Hybrid, Deep learning, Traffic flow prediction, Traffic forecasting, CNN, RNN, LSTM


## 1. INTRODUCTION

Deep neural network theories and methods were recently fast developed and widely applied in different areas. One of the most important application is in *traffic flow prediction*[14], which is also known as *traffic forecasting*[2].

The problem of traffic flow prediction is to predict *the traffic flow rates*, i.e., number of cars per minute for a specific location in the traffic network based on the historical and current traffic flow data, trajectory data, weather, social event etc. The traffic system data can further include fine-grained traffic network topology, weather information, car speed, travel time information etc. This is a typical big data driven state forecasting problem for large dynamic systems, and is a fundamental problem in transportation system scheduling and optimization. For these reasons, DNN based traffic flow prediction has attracted great research attentions in recent years [26, 22, 25, 13]. The traffic flow rates are affected by information of different dimensions:

1. *Temporal dimension*, the traffic flow has typical time dependent features, which varies with time. In working days there are traffic hours and the traffic patterns in working days and weekends are different. Therefore, time is an important factor in traffic flow prediction.
2. *Spatial dimension*, the traffic flow varies at different locations. Different locations may have different traffic flow features over time.
3. *Events*, the environment information such as weather and social events also greatly impact the traffic flow.

These information make traffic flow highly dynamic over time, space, but have some interior rules which drive the variation of traffic flows at different time and locations. Traditional traffic flow prediction methods generally employ machine learning to mine the interior rules. Related methods include K-NN[4], ARIMA[1], SVR[16], neural networks[8], graph optimization[17][19] etc. We call these methods *shallow model*. A survey of these methods can be referred to [9].

With the fast development of deep neural network (DNN) theory and applications, the autonomous feature extraction characteristics of deep learning has been exploited to conduct DNN based traffic flow prediction. Researchers found that DNN-based traffic flow prediction can have better accuracy than traditional methods[26, 22, 25, 13]. Convo-


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lution Neural Network (CNN)[26], Stacked Auto-Encoder (SAE)[25], Recurrent Neural Networks (RNN)[15], and Long Short-Term Memory units (LSTMs)[5] are investigated to train deep learning model for traffic flow prediction.

However, different DNN models have different specialties. For example, CNN is better in capturing the spatial dependency in the transportation network; RNN and LSTM are better in capturing the temporal dependencies; LSTM can also capture long-term temporal dependency. SAE is better in extracting latent features from the raw data. Since the traffic flow variation depends both on the temporal and spatial data, a hybrid composition of different DNN models becomes a popular approach in recent years to improve the traffic forecasting accuracy.

This paper is the first work to give a thorough survey of state of the art hybrid DNN models for traffic flow prediction. The main contributions are as following:

1. We summarize the different types of data sources used in DNN-based traffic flow prediction methods.
2. From simple composition to complex composition, we classify the hybrid DNN-based traffic prediction methods into five categories and introduce the representative methods in each category.
3. We summarize and compare the performances of representative DNN based traffic flow prediction methods.

The rest of this paper is organized as following. The data sources used in deep learning based traffic flow prediction are introduced in Section 2. Survey of hybrid DNN traffic prediction models is presented in Section 3. The paper is concluded with discussions in Section 4.

## 2. DATA SOURCES FOR HYBRID DNN

The DNN-based traffic flow prediction problem is data driven, therefore, data source plays an important role in the DNN-based traffic flow prediction problem. Especially for the design of hybrid DNN models, different models generally utilize different kinds of data sources to extract features in different dimension. Feature fusion is then conducted to combine learned dependencies from different data sources.

Before introducing the data sources, at first, a transportation network is generally modelled by a graph $G = (V, E)$, every node $v \in V$ is either a road cross, a road entrance or a road end. An edge $(i, j) \in E$ if vertex $i$ and $j$ are directly connected without other vertices between them. Traffic flow is defined as the number of cars flowed through each edge during a given time interval. The data sources used for traffic prediction include:

1. *Historical traffic flows.* The most widely used data source for traffic flow prediction is the historical traffic flows at different locations. Suppose we are interested at the traffic flows of $n$ edges in the road network. The historical traffic flows of edge $i$ is denoted by $\mathbf{x_i} = \{x_{i,t-T_d}, x_{i,t-T_d+1}, \cdots, x_{i,t}\}^T$. The goal of traffic flow prediction is to predict the traffic flows at time $t + T_p$ of these $n$ edges based on their historical traffic flows and the network structure. This leads to the following traffic prediction model:

$$\mathbf{X}_p = \begin{pmatrix} x_{1,t+T_p} \\ \vdots \\ x_{n,t+T_p} \end{pmatrix} = f\left(\mathbf{X}_h, G(V,E)\right) \qquad (1)$$

where $\mathbf{X}_h = \begin{pmatrix} x_{1,t-T_d} & x_{1,t-T_d+1} & \dots & x_{1,t} \\ \vdots & \vdots & \cdots & \vdots \\ x_{n,t-T_d} & x_{n,t-T_d+1} & \cdots & x_{n,t} \end{pmatrix}$.
For inputting the traffic flow to RNN and CNN, the traffic flow and transition graph are generally converted to 1D, 2D vectors or tensors[27][11].

2. *OBD data.* The on-board device OBD is a car embedding device, which includes a real-time communication system; each OBD recognizes the location of the probe vehicle using real-time Global Positioning System (GPS) technology, and computes an average link travel speed when the probe vehicle completes a specified link between intersections. The OBD data can be firstly processed to calculate the traffic flow in [18]. The traffic speed can also be directly used as input of prediction models[8][11].

3. *Weather data.* Weather information also has great impacts to the traffic speed. Some existing works consider weather information when building the prediction model[23][27, 24]. The learning model can then represented by $\mathbf{X}_p = f\left(\mathbf{X}_h, G(V,E), W\right)$.

4. *Social events.* Social events, such as sport events, national celebration events have great impacts to traffic flow speeds. [21] investigate the traffic flow variations during to special social events. [27] proposed multi-task learning which addresses the social events' impacts.

5. *Speed, Journey Time, Accidents.* The trajectory data of cars, including average speed, journey time are also used in building multi-mode DNN model[6, 5, 21, 11, 8]. The accidents are also considered in hybrid models[12].

Table 1: Data sources used in deep learning based traffic flow prediction

| Data Source | Related Work |
|---|---|
| Historical traffic flow | most of deep learning based traffic flow prediction models [14] [2][23][11][10][25] etc. |
| OBD data | [18] |
| Weather data | [27, 24] [23] |
| Social events, Accidents | [21][12] [27] |
| Trajectory, Speed | [6, 5, 21, 11, 8] |

Table 1 summarizes the data sources used in deep learning based traffic flow prediction methods. How to deal with the noisy data was reported in [3].

## 3. HYBRID PREDICTION MODELS

Based on different type of data sources, various hybrid deep learning models for traffic prediction have been proposed and investigated. We summarizes the related works into five categories.

### 3.1 Stacked Learners+FCN

First kind of hybrid DNN network is the composition of Stacked Deep Networks, such as AE, CNN, LSTM with Fully Connected Neural Network layers.

Zhang et al. [26] propose convolution neural network (CNN) deep learning framework. In the proposed framework, the optimal input data time lags and amounts of spatial data are determined by a spatio-temporal feature selection algorithm (STFSA), and selected spatio-temporal traffic flow features are extracted from actual data and converted into a two-dimensional matrix. The CNN then learns these features to construct a predictive model. The outputs of CNNs are input to Fully Connected Networks (FCN) to predict the future traffic flow.

Lv et al. [22] propose to train Stacked Auto-Encoder (SAE) in layered fashion firstly to learn generic traffic flow features, and the auto-encodes are then connected into stacks and are connected to a fully connected output layer for a fine turning of the SAE parameters and to predict the traffic flow.

Zhang et al. [25] propose a SAE+FCN network as shown in Fig.1. The encoder first obtains a vector representation of historical congestion levels of a transportation network and their correlations using four encoding layers. Next the decoder builds a representation of the congestion levels for a future time point using four decoding layers. Then two dense layers construct the congestion levels for each grid in that transportation network at future time point.

Parnami et al. [13] propose stacked LSTM + FCN to learn the dependencies of different time periods. Zou et al. propose [28] LSTM model with different dimensions of historical data for accurate prediction of city scale traffic flows.

Cui et al. [5] propose a deep stacked bidirectional and unidirectional LSTM (SBU-LSTM) neural network. It considers both forward and backward dependencies of time series data to predict the network-wide traffic speed.

## 3.2 CNN+RNN

It is shown that CNN is better in capturing spatial dependency while RNN is better for capturing temporal dependency. Therefore, composition of CNN and RNN becomes a popular approach to extract the spatial-temporal features in traffic flow prediction.

Lv et al.[11] proposed a LC-RNN framework. It takes advantage of both RNN and CNN models by a rational integration of them, so as to learn more meaningful time-series patterns that can adapt to the traffic dynamics of surrounding areas. The system architecture of LC-RNN network is shown in Fig.2. The network takes the speed vectors of intervals in the recent time and the topology of road network as inputs. These input data is firstly processed by a series of Look-up Convolution (LC) layers. The convolution layer can extract the spatial dependency features from the input data. Since the speed of one road will be affected by traffic condition from more distance areas, a stack of LC layers is used to understand more distance spatial evolution. Meanwhile, Batch Normalization (BN) is added after each LC layer for faster training speed. After getting the spatial traffic evolution patterns, these features are converted into time sequence to feed into RNN layer. LSTM model is used as the RNN model to capture the long term dependency. The output is denoted $Y_{ST}$. In addition, fully-connected (FC) layers are used to learn the daily/weekly periodicity to obtain periodical patterns $Y_P$. Context factors such as weather, holiday are extracted as $Y_C$ by another two-layer FC neural networks. At last, a parameter-matrix-based method to fuse $Y_{ST}, Y_C$ and $Y_P$.

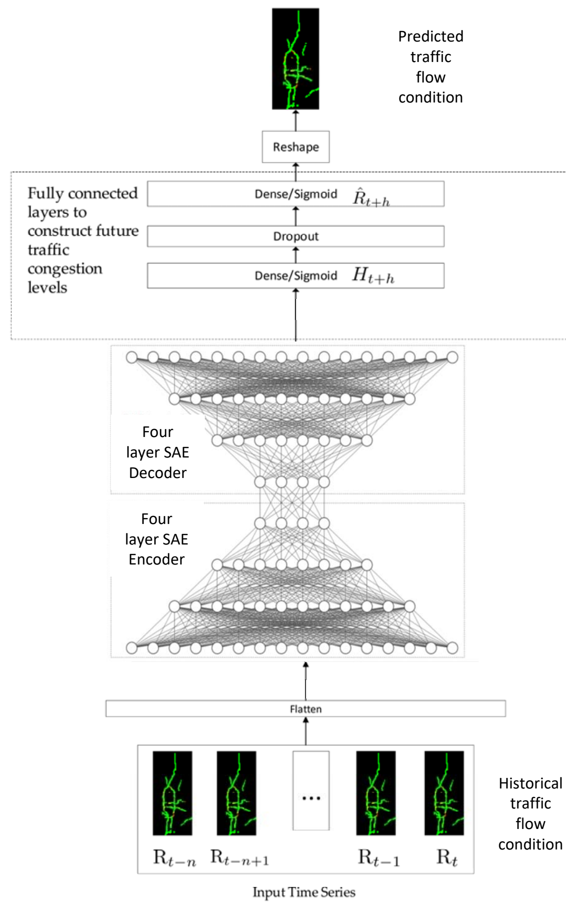


Figure 1: Hybrid SAE and FCN model for traffic flow prediction[25]

Yang et al. [21] propose a hybrid convolutional long short-term memory neural network model based on critical road sections (CRS-ConvLSTM NN) to predict the traffic evolution of global networks. The critical road sections that have the most powerful impact on the subnetwork are identified by a spatiotemporal correlation algorithm. Subsequently, the traffic speed of the critical road sections is used as the input to the ConvLSTM to predict the future traffic states of the entire network.

Han et al.[7] propose a parallel spatiotemporal deep learning network for highway traffic flow forecasting. In it, a convolutional neural network is used to extract spatial features and long short-term memory is used to extract temporal features of traffic flow. The outputs of CNNs and LSTMs are concatenated to produce the future traffic flow.

## 3.3 CNN+RNN+Attention

Wu et al. [20] propose a hybrid traffic flow prediction model based CNN, RNN and an attention scheme that automatically learns to determine the importance of past traffic flow. A fully-connected neural network was designed to learn the weights of how strong the input flow of past spatial-temporal position $S^t$ correlates to the future traffic flow. The learned weights are represented by a matrix $\mathbf{A}$, with the same size of the historical data $\mathbf{S^f}$. Then the traffic flow

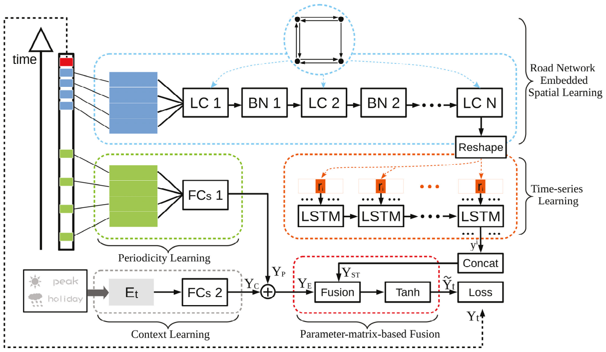


Figure 2: Hybrid SAE and FCN model for traffic flow prediction[11]

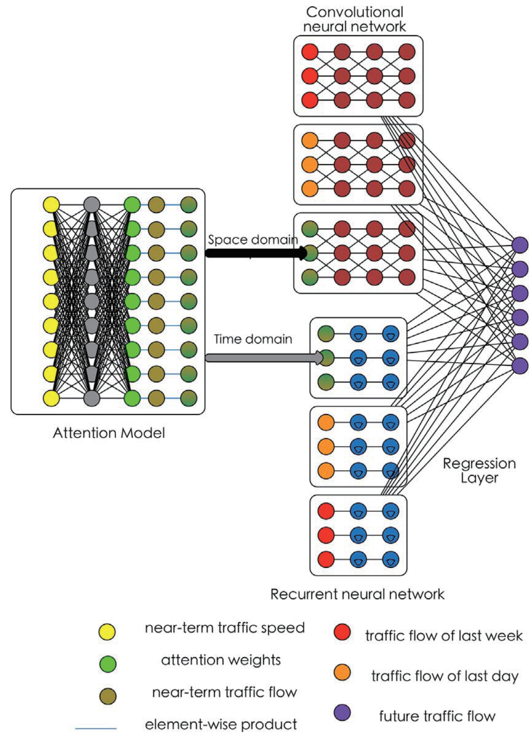


Figure 3: Traffic flow prediction using CNN, GRU and an Attention scheme[20]

matrix $\mathbf{S^f}$ is point-wise multiplied with the attention matrix $\mathbf{A}$ to obtain a weighted traffic flow matrix $\mathbf{S^A}$ for deeper learning procedures. The spatial features are then mined by CNN and the temporal features are learned by Gated Recurrent Unit Neural network (GRU). The workflow of the CNN+RNN+attention model is shown in Fig.3.

### 3.4 Embedding+CNN+RNN

Zheng et al.[27] propose a deep and embedding learning approach (DELA) that can help to explicitly learn from fine-grained traffic information, route structure, and weather conditions. The DELA framework consists of an embedding component, a convolutional neural network (CNN) component and a long short-term memory (LSTM) component. The embedding component captures the categorical feature information and identify correlated features; the CNN component learns from the 2-D traffic flow data while the LSTM component has the benefits of maintaining a long-term memory of historical data. The integration of the three models in DELA together improves the prediction accuracy of traffic flow. Fig.4 shows the architecture of the DELA framework. The fine-grained weather data and route structure are firstly preprocessed to extract the categorical factors including precipitation, temperature and route structure etc. These categorical factors are input into the embedding component. The traffic flow data is converted to 1D and 2D streams to be fed to LSTM component and CNN component respectively. The normalization results of these three components are fused by the ReLU function as the output.

### 3.5 Multi-task Learning

Zhang et al. [24] separate the flow into in-flow to node and flows on edge that between nodes. The flow prediction is therefore to predict both the in-flow of nodes and inter-flow among nodes. To address this problem, a multi-task deep-learning framework that simultaneously predicts the node flow and edge flow throughout a spatio-temporal network is proposed. They design two sophisticated models, i.e., NodeNet and EdgeNet for predicting node flow and edge flow respectively as shown in Fig.5. Both NodeNet and EdgeNet contain three feed forward convolution nework (3S-FCN), which mine features in closeness, period and trend respectively. These two network models are connected by coupling their latent representations of middle layers at a bridge node, and trained together. The external factor is also integrated into the framework through a gating fusion mechanism. In the edge flow prediction model, they employ an embedding component to deal with the sparse transitions between nodes.

In the input of the two network, both the trajectory data and time-varying transition graph are converted to tensors for working as input of FCN.

### 3.6 Summary of Hybrid DNN Models for Traffic Flow Prediction

From above review, we can see that the hybrid DNN models for traffic flow prediction are becoming more and more complex for better utilizing the temporal and spatial dependencies in the traffic flow data. From simple model to complex one, we summarize the state of the art of related hybrid DNN models for traffic forecasting into Table2.

## 4. CONCLUSION AND DISCUSSION

For the fast development of deep learning theories and applications, and for the spatial and temporal dependency features of traffic flow data, hybrid deep learning models for traffic flow prediction attract great attentions in recent years. This work presents a thorough review of hybrid deep learning models for traffic flow prediction. It firstly introduces the various data sources used in hybrid models for traffic flow prediction and then introduces the hybrid traffic flow prediction models from simple ones to the complex ones. By reviewing state-of-the-art models, we can see that the hybrid models for traffic flow prediction is becoming more and more complex for capturing more details in the transportation data. With the increasing collection of more fine-grained, multi-type data from transportation systems,

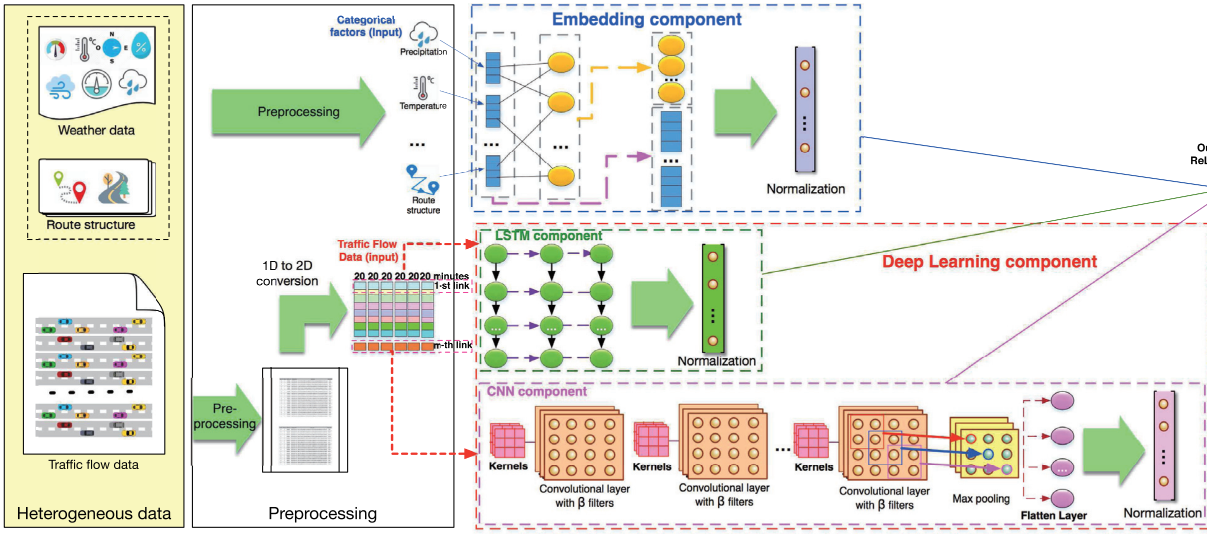


Figure 4: Deep and Embedding Learning Approach (DELA).[27]

Table 2: Summary and comparison of hybrid DNN models for traffic prediction

| Model Description | References | Temporal | Spatial | Weather Data | Events |
|---|---|---|---|---|---|
| CNN + FCN | Zheng et al.[26] | | ✓ | | |
| SAE + FCN | Lv. et al. [22], Zhang et al. [25] | ✓ | ✓ | | |
| Stacked LSTM | Zou et al. [28] | ✓ | | | |
| LSTM+FCN | Parnami et al. [13] | ✓ | | | |
| CNN + RNN | Lv et al.[11],Yang et al. [21], Han et al.[7] | ✓ | ✓ | | [21] |
| CNN+RNN+Attention | Wu et al. [20] | ✓ | ✓ | | ✓ |
| CNN+RNN+Embedding | Zheng et al.[27] | ✓ | ✓ | ✓ | ✓ |
| Multi-task Learning | Zhang et al. [24] | ✓ | ✓ | ✓ | |

in the future work, it can be expected that the hybrid deep learning model will continuously evolve to capture more data features, to provide more accurate and scalable traffic flow prediction capability.

## 5. ACKNOWLEDGMENTS

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## 6. REFERENCES

[1] Application of Subset Autoregressive Integrated Moving Average Model for Short-Term Freeway Traffic Volume Forecasting - Sangsoo Lee, Daniel B. Fambro, 1999.

[2] Albertengo, G., and Hassan, W. Short Term Urban Traffic Forecasting Using Deep Learning. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences IV-4/W7* (Sept. 2018), 3–10.

[3] Ao, B., Wang, Y., Yu, L., Brooks, R. R., and Iyengar, S. On precision bound of distributed fault-tolerant sensor fusion algorithms. *ACM Computing Surveys (CSUR) 49*, 1 (2016), 5.

[4] Cai, P., Wang, Y., Lu, G., Chen, P., Ding, C., and Sun, J. A spatiotemporal correlative k-nearest neighbor model for short-term traffic multistep forecasting. *Transportation Research Part C: Emerging Technologies 62* (Jan. 2016), 21–34.

[5] Cui, Z., Ke, R., and Wang, Y. Deep Stacked Bidirectional and Unidirectional LSTM Recurrent Neural Network for Network-wide Traffic Speed Prediction. 9.

[6] Dauwels, J., Aslam, A., and et al. Predicting traffic speed in urban transportation subnetworks for multiple horizons. In *2014 International Conference on Control Automation Robotics & Vision* (Singapore, Dec. 2014), IEEE, pp. 547–552.

[7] Han, D., Chen, J., and Sun, J. A parallel spatiotemporal deep learning network for highway traffic flow forecasting. *International Journal of Distributed Sensor Networks 15*, 2 (Feb. 2019).

[8] KanestrÃŸm, P. y. Traffic flow forecasting with deep learning.

[9] Li, Y., and Shahabi, C. A brief overview of machine learning methods for short-term traffic forecasting and future directions. *SIGSPATIAL Special 10*, 1 (June 2018), 3–9.

[10] Lv, Y., Duan, Y., Kang, W., Li, Z., and Wang, F.-Y. Traffic Flow Prediction With Big Data: A Deep Learning Approach. *IEEE Transactions on Intelligent Transportation Systems 16*, 2 (Apr. 2015).

[11] Lv, Z., Xu, J., Zheng, K., Yin, H., Zhao, P., and

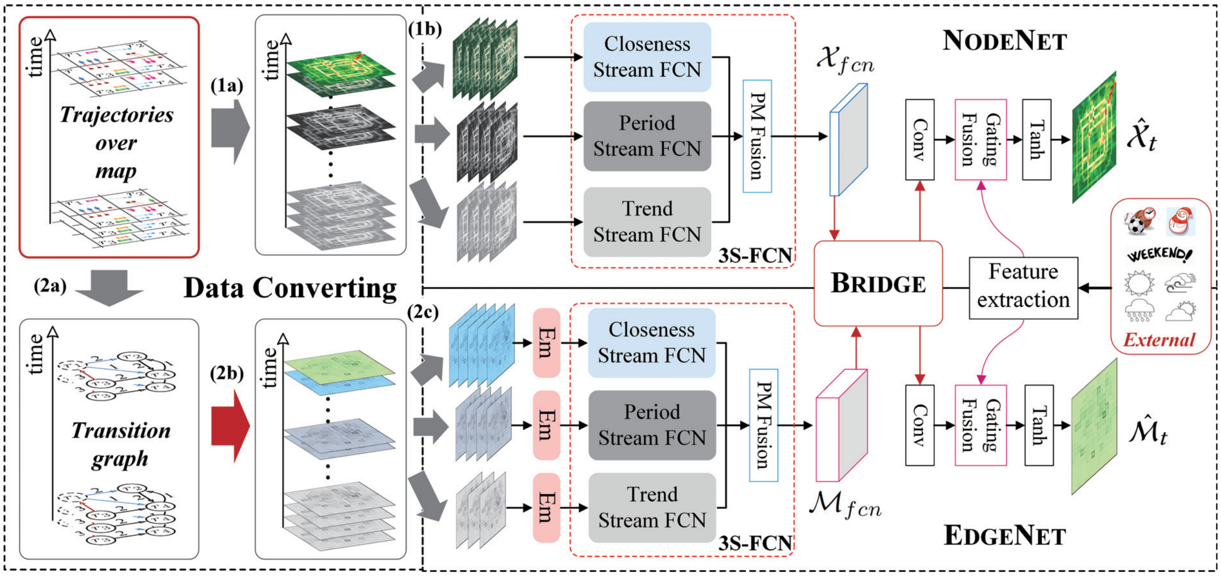


Figure 5: MDL framework. Em: embedding; Conv: convolution; FCN: fully convolutional network.[24]

Zhou, X. LC-RNN: A Deep Learning Model for Traffic Speed Prediction. 7.

[12] Manoharan, S. Short Term Traffic Flow Prediction Using Deep Learning Approach. Master's thesis, Dublin, National College of Ireland, Dec. 2016.

[13] Parnami, A., Bavi, P., Papanikolaou, D., Akella, S., Lee, M., and Krishnan, S. Deep Learning Based Urban Analytics Platform: Applications to Traffic Flow Modeling and Prediction. 9.

[14] Polson, N. G., and Sokolov, V. O. Deep learning for short-term traffic flow prediction. *Transportation Research Part C: Emerging Technologies 79* (June 2017), 1–17.

[15] Shafqat, W., Malik, S., Byun, Y.-c., and Kim, D.-H. A Short-Term Traffic Flow Prediction Based on Recurrent Neural Networks for Road Transportation Control in ITS. 5.

[16] Su, H., Zhang, L., and Yu, S. Short-term Traffic Flow Prediction Based on Incremental Support Vector Regression. In *Third International Conference on Natural Computation (ICNC 2007)* (Aug. 2007), vol. 1, pp. 640–645.

[17] Sun, T., Wang, Y., Li, D., Gu, Z., and Xu, J. Wcs: Weighted component stitching for sparse network localization. *IEEE/ACM Transactions on Networking (TON) 26*, 5 (2018), 2242–2253.

[18] Wang, P.-w., Yu, H.-b., Xiao, L., and Wang, L. Online Traffic Condition Evaluation Method for Connected Vehicles Based on Multisource Data Fusion, 2017.

[19] Wang, Y., Sun, T., Rao, G., and Li, D. Formation tracking in sparse airborne networks. *IEEE Journal on Selected Areas in Communications 36*, 9 (2018), 2000–2014.

[20] Wu, Y., Tan, H., Qin, L., Ran, B., and Jiang, Z. A hybrid deep learning based traffic flow prediction method and its understanding. *Transportation Research Part C: Emerging Technologies 90* (May 2018), 166–180.

[21] Yang, G., Wang, Y., Yu, H., Ren, Y., and Xie, J. Short-Term Traffic State Prediction Based on the Spatiotemporal Features of Critical Road Sections. *Sensors (Basel, Switzerland) 18*, 7 (July 2018).

[22] Yisheng, L., Duan, Y., Kang, W., Li, Z., and Wang, F.-Y. Traffic Flow Prediction With Big Data: A Deep Learning Approach. *IEEE Transactions on Intelligent Transportation Systems 16* (Jan. 2014), 865–873.

[23] Zhang, D., and Kabuka, M. R. Combining Weather Condition Data to Predict Traffic Flow: A GRU Based Deep Learning Approach. In *2017 IEEE 15th International Conference on Dependable, Autonomic and Secure Computing* (Mar. 2018), pp. 1216–1219.

[24] Zhang, J., Zheng, Y., Sun, J., and Qi, D. Flow Prediction in Spatio-Temporal Networks Based on Multitask Deep Learning. *IEEE Transactions on Knowledge and Data Engineering* (2019), 1–1.

[25] Zhang, S., Yao, Y., Hu, J., Zhao, Y., Li, S., and Hu, J. Deep Autoencoder Neural Networks for Short-Term Traffic Congestion Prediction of Transportation Networks. *Sensors (Basel, Switzerland) 19*, 10 (May 2019).

[26] Zhang, W., Yu, Y., Qi, Y., Shu, F., and Wang, Y. Short-term traffic flow prediction based on spatio-temporal analysis and CNN deep learning. *Transportmetrica A: Transport Science 15*, 2 (Nov. 2019), 1688–1711.

[27] Zheng, Z., Yang, Y., Liu, J., Dai, H., and Zhang, Y. Deep and Embedded Learning Approach for Traffic Flow Prediction in Urban Informatics. *IEEE Transactions on Intelligent Transportation Systems* (2019), 1–13.

[28] Zou, Z., Gao, P., and Yao, C. City-Level Traffic Flow Prediction via LSTM Networks. ICAIP '18, ACM, pp. 149–153. event-place: Chengdu, China.