Short-Term Traffic Prediction: Modelling Temporal-Spatial Features in Local Highway Networks with Deep Neural Networks

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Abstract

Both temporal and spatial features provide significant implications for short-term traffic volume prediction. The problem is challenging due to various non-linear temporal dynamics at different locations, complicated spatial dependencies and difficulty for longer-step ahead forecasting. We propose two deep learning models, CNN-LSTM with attention mechanism (CNN-LSTM-Attn) and Temporal-Spatial-LSTM (TS-LSTM) to incorporate temporal and spatial correlations. Experiments show that both models outperform baselines on the Highways England dataset and the CNN-LSTM-Attn achieves lowest MAPE 9.26% on 2-hour traffic volume prediction. We also evaluate the CNN-LSTM-Attn on the KDDCUP17 dataset and our model defeats the model that got first place in the competition with lower MAPE 10.48%. Our models achieve 2-hour forecasting, which is longer than previous literature, with outstanding accuracy and robustness.
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Chapter 1

Introduction

Short-term traffic volume prediction can be essential for Intelligent Transportation Systems (ITSs), traffic management authorities and travellers. During peak hours, accurate prediction and abnormal traffic detection can be especially important for authorities to regulate specific crowded roads and travellers to choose proper routes. Many navigation services have already integrated ETA (Estimated Time of Arrival) calculation services but circumstances in different places can be locally various. Traffic flow prediction has become a challenging task due to various non-linear temporal dynamics at different locations, complicated underlying spatial dependencies and difficulty for longer-step ahead forecasting. Besides, traffic can be potentially influenced by lots of environmental and artificial factors, such as weather, holidays, special events, accidents, and etc..

More sensors and cameras, which have been deployed along roads and the number of which increases rapidly in recent years, make it possible to collect huge amount of data for traffic analysis, though measurement error can be a concern. With the increasing popularity of Internet of Things (IoT), not only larger amount of data and also data from variety of new domains can be expected in the future. In addition to the abundance of data and sources, the exponentially growing computing power allows researchers to implement and run more complex models with efficiency.

Mathematically, the short-term traffic volume prediction can be formalised as follows. Let $x_t$ be one observation of traffic volume at timestamp $t$ at a specific location. Given a sequence of observations $\{x_1, x_2, ..., x_t\}$, a model $\mathcal{M}$ with its parameters $\theta$ outputs prediction of observations in the following time period $\{x_{t+1}, x_{t+2}, ..., x_{t+H}\}$ with highest probability.

$$\hat{x}_{t+1}, \hat{x}_{t+2}, ..., \hat{x}_{t+H} = \arg \max_{x_{t+1}, x_{t+2}, ..., x_{t+H}} P(x_{t+1}, x_{t+2}, ..., x_{t+H} | x_1, x_2, ..., x_t; \mathcal{M}; \theta) \quad (1.1)$$
Considering spatial correlation among different locations, we can further define a \( K \times T \) matrix \( \{X_1, X_2, ..., X_T\} \) which include observations at \( K \) locations. The traffic prediction problem with both temporal and spatial information can be rewritten as:

\[
\hat{X}_{t+1}, \hat{X}_{t+2}, ..., \hat{X}_{t+H} = \arg \max_{X_{t+1}, X_{t+2}, ..., X_{t+H}} P(X_{t+1}, X_{t+2}, ..., X_{t+H}|X_1, X_2, ..., X_t; \mathcal{M}; \theta)
\]

Previous literature analysed short-term traffic prediction commonly based on three approaches, namely classic time series analysis, machine learning and data assimilation. Box et al. (2015) introduces a family of time series analysis methods, especially SARIMA and VAR which are popular choices in traffic prediction. Lippi et al. (2013) quantitatively compares performance of non-parametric (random walk, seasonal mean) and parametric models (SARIMA, ARIMA, SVR, ANN), and SARIMA achieves overall best accuracy. Kamarianakis and Prastacos (2003, 2005) incorporate spatial correlation among neighbouring locations and achieve promising results by VAR and space-time ARIMA (STARIMA). Sun et al. (2006) proposes a new approach based on Bayesian Network and treats the joint probability distribution between the cause node and the effect node as a Gaussian mixture model. Besides, Kalman Filter has also been applied for traffic prediction. Considering observations and models are neither assumed to be accurate due to underlying factors that may be unknown, data assimilation methods, e.g. Kalman Filter, can be helpful to balance observations and prior models, and estimate real values in series with posterior distribution. Okutani and Stephanedes (1984); Xie et al. (2007) have shown promising results of Kalman Filter in traffic volume prediction problem. Guo et al. (2014) introduces adaptive Kalman Filter to improve stability and real-time processing for SARIMA+GARCH structure. In addition to the three popular approaches, Xue and Shi (2008) introduces chaos time series theory with two-step optimization for traffic volume forecasting and Yang et al. (2014) demonstrates similarity search in historical traffic database can improve prediction accuracy.

Recent research interest on traffic prediction has been moved to deep learning models. Chen et al. (2016) proposes a hybrid method combining KNN and fully connected neural network and suggests its advantage in highways traffic prediction. Duan et al. (2016) utilises RNN with LSTM on highways traffic time prediction and achieve good accuracy on 1-step ahead prediction. Shahsavari and Abbeel (2015) uses graph neural networks which is able to extract non-linear spatial and temporal relations in transportation network. Similarly, Li et al. (2017) proposes a graph convolutional RNN to capture both spatial and temporal correlations.

The tasks in this project aim to forecast traffic volume in the next 2 hours in highways network based on historical observations. Prior data analysis have demonstrated consistent temporal seasonality, special patterns on special days as well as significant spatial correlation among neighbouring locations. We propose two deep learning models, CNN-LSTM with temporal attention mechanism (CNN-LSTM-Attn)
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and Temporal-Spatial-LSTM (TS-LSTM) with spatial relational module, to model
temporal and spatial dependencies on traffic flow. The CNN-LSTM-Attn outperforms
the baselines with lowest MAPE 9.26% on the Highways England dataset and de-
feats the model that got first place in the KDDCUP17 competition with lower MAPE
10.48%.

The contributions of this projects can be summarised as below:

1. The CNN-LSTM-Attn is able to extract temporal dependencies without supervi-
sion. Though traffic patterns at different locations are various, the CNN-LSTM-
Attn is general and only one model is needed for the whole transportation
network.

2. The TS-LSTM can incorporate both temporal and spatial dependencies among
neighbouring locations and is not necessarily privy to which spatial relation
may exist nor the actual meaning of particular relation.

3. Our models can predict 2-hour ahead observations in the future which is longer
than that in previous literature (commonly prediction within 30 minutes).

4. The data analysis quantitatively demonstrates and visualises temporal patterns
and spatial correlations in the transportation network.

In the Chapter 2, we will introduce background information and related literatures
of baselines and deep learning. The Chapter 3 will firstly introduce the datasets we
use and then demonstrate discovery on temporal patterns and spatial correlations.
Our proposed methodologies based on deep learning and the implementation of our
learning models will be covered in the Chapter 4. Experiments and evaluation of our
methodologies as well as the visualisation system will be introduced in the Chapter
5. We will finally summarise conclusions and future works in the Chapter 6.
Chapter 2

Background

The traffic prediction problem can be defined as given a sequence \( \{x_1, x_2, ..., x_t\} \) of traffic observations (time, speed, volume, etc.) at a specific location, estimation of \( x_{t+\Delta} \) with forecasting horizon \( \Delta \) need to be predicted. With underlying spatial correlations, the \( x_{t+\Delta} \) can also be influenced by neighbouring locations in the transportation network. This chapter provides an overview of literatures and detailed introduction of related methods on traffic forecasting tasks. In this chapter, we will firstly introduce classical time series analysis methods and machine learning models which are implemented as baselines, and then fundamental deep neural network architectures that our proposed models are based on.

2.1 ARMA Family

The famous work, originally published in 1970 and republished by Box et al. (2015), proposes a family of classical time series analysis methods, especially the popular autoregressive moving average (ARMA) and its generalizations. Lippi et al. (2013) implemented a quantitative comparison among ARMA and its family with other methods on traffic flow forecasting and SARIMA (Seasonal Auto-Regressive Integrated Moving Average) with Kalman Filter achieves overall best performance but requires high computational resources. In this section, we will introduce ARMA and its family mathematically.

2.1.1 ARMA

Autoregressive moving average, represented by \( ARMA(p, q) \), consists of two parts, which are an autoregressive \( AR(p) \) model and a moving-average \( MV(q) \) model. Typ-
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2.1. ARMA FAMILY

ically, the ARMA is a linear model and can be used to understand and predict values in time series.

**Autoregressive model** If a Gaussian random noise is assumed, the conditional probability of \( x_t \) can be written as

\[
p(x_t | x_1, \ldots, x_{t-1}, \epsilon_t) \sim \mathcal{N}(f(x_1, \ldots, x_{t-1}), \sigma^2)
\]

\[
x_t = f(x_1, \ldots, x_{t-1}) + \epsilon_t
\]

where \( \epsilon_t \) is an independent white noise and \( f \) is a regression function. In autoregressive model, given a integer \( p \), the AR(\( p \)) model is a linear combination of previous values with a random noise term, and is defined as:

\[
x_t = c + \sum_{i=1}^{p} \psi_i x_{t-i} + \epsilon_t
\]

where \( c, \psi_1, \ldots, \psi_p \) are parameters and \( \epsilon_t \sim \mathcal{N}(0, \sigma^2) \). A future estimation \( x_t \) linearly depends on past observation \( \{x_{t-p}, \ldots, x_{t-1}\} \). With lag operator, the model can be equivalently written as:

\[
x_t = c + \sum_{i=1}^{p} \psi_i B^i x_t + \epsilon_t
\]

As classic AR is a linear model, kernel functions can be applied to incorporate non-linear dependence relations. For example, RBF kernel is popular in traffic problems (Wu et al. (2004); Sun and Chen (2008); Wang et al. (2009); Lippi et al. (2013)) and the regression function can be formatted as:

\[
x_t = c + \sum_{j=1}^{h} \psi_j \phi_j(x_{t-1}, \ldots, x_{t-p})
\]

**Moving-Average model** The moving-average model captures dependence relations between variables and unobserved noise. The conditional probability is defined as \( p(x_t | \epsilon_{t-q}, \ldots, \epsilon_t) \). As \( \epsilon_i \) are unobservable, the interpretability of moving-average model is less convincing than the autoregressive model. Given a integer \( q \), the MV(\( q \)) is defined as:

\[
x_t = \mu + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}
\]

where \( \mu \) is an expectation of \( x_t \), \( \theta_1, \theta_2, \ldots, \theta_q \) are parameters and \( \epsilon_t, \epsilon_{t-1} \) are white noise term. The MV(\( q \)) model is typically a linear regression of current expectation with current and previous white noise. It can be equivalently written with lag operator:

\[
x_t = \mu + \epsilon_t (1 + \sum_{i=1}^{q} \theta_i B^i)
\]
ARMA The $ARMA(p, q)$ as illustrated in Figure 2.1, is a summation of $AR(p)$ and $MV(q)$, modelling conditional probability $p(x_t|x_{t-1}, ..., x_{t-p}, \epsilon_t, ..., \epsilon_{t-q})$, defined as:

$$x_t = c + \epsilon_t + \sum_{i=1}^{p} \psi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

$$= c + \sum_{i=1}^{p} \psi_i B^i x_t + \epsilon_t (1 + \sum_{i=1}^{q} \theta_i B^i)$$  \hspace{1cm} (2.8)

Alternatively the ARMA can be written with lag operator:

$$\psi(B)x_t = c + \theta(B)\epsilon_t$$

where $\psi(B) = 1 - \sum_{i=1}^{p} \psi_i B^i$ \hspace{1cm} (2.9)

$$\theta(B) = 1 + \sum_{i=1}^{q} \theta_i B^i$$

\[\psi(B)(1 - B)^d x_t = c + \theta(B)\epsilon_t \] \hspace{1cm} (2.10)

\[\text{Figure 2.1: An illustration of dependence and independence in } ARMA(2,2). \text{ Given } \{x_{t-2}, x_{t-1}, \epsilon_{t-1}, \epsilon_{t-1}, \epsilon_t\}, x_t \text{ is independent with other previous values.}\]
2.1.2 SARMA

**Seasonal ARMA** A key nature of traffic data is periodic features. As traffic can be potentially significantly affected by holidays and working hours, the periodicity of traffic peak and off-peak flow patterns can help to improve accuracy of prediction. In ARMA, \( x_t \) is independent with \( \{ x_1, ..., x_{t-p-1} \} \), if given \( \{ x_{t-p}, ..., x_{t-1} \} \). SARMA, as shown in Figure 2.2, introduces a group of hyper-parameters \( (P,Q) \) \( S \), which defines dependence between \( x_t \) with \( \{ x_{t-S}, ..., x_{t-PS}, \epsilon_{t-S}, ..., \epsilon_{t-QS} \} \). The SARMA denoted by \( SARMA(p,q) \times (P,Q) \) \( S \), can be defined as:

\[
\begin{align*}
\Psi(B^S) \psi(B)x_t &= c + \Theta(B^S) \theta(B) \epsilon_t \\
\text{where} \quad \Psi(B^S) &= 1 - \sum_{i=1}^{P} \psi_i B^{iS} \\
\Theta(B^S) &= 1 + \sum_{i=1}^{Q} \Theta_i B^{iS}
\end{align*}
\]  

\( (2.11) \)

\[ \text{Figure 2.2: An illustration of dependence and independence in } SARMA(2,2) \times (1,1)_S. \]  

\( x_t \) not only depends on previous neighboring values and also takes seasonality into account.

**SARIMA** Similarly, SARIMA can be denoted as \( SARIMA(p,d,q) \times (P,D,Q) \) \( S \), and defined as:

\[
\begin{align*}
\Psi(B^S) \psi(B)(1 - B)^d(1 - B^S)^D x_t &= c + \Theta(B^S) \theta(B) \epsilon_t \\
\end{align*}
\]  

\( (2.12) \)

2.1.3 VAR

Vector autoregressive models (VAR) is a special case of vector ARMA and is capable of capturing linear interdependencies among multiple time series (see also Box et al. 7...
Given \( K \times T \) multivariate time series \( \{X_1, X_2, ..., X_T\} \), VAR can be defined as:

\[
X_t = A_1X_{t-1} + A_2X_{t-2} + ... + A_pX_{t-p} + \varepsilon_t
\]  

(2.13)

where \( A_i \) is \( K \times K \) coefficient matrix and \( \varepsilon_t \sim \mathcal{N}(0, \Sigma_K) \). In a transportation network, considering that each node has a traffic series, VAR can be used to find spatial relations among multiple nodes. Kamarianakis and Prastacos (2003, 2005) incorporate spatial information into traffic prediction tasks and demonstrate promising results by VAR and space-time ARIMA (STARIMA).

### 2.1.4 Autocorrelation

**Autocorrelation Function (ACF)** Repeating pattern of a given sequence helps to analyse and forecast, especially in traffic prediction which has strong seasonality. Autocorrelation, also called serial correlation, measures similarity between observations and observations with previous time steps, also called lags. In statistics, the autocorrelation is a function of the time lag and autocorrelation at lag \( k \) is defined as

\[
\rho_k = \frac{\mathbb{E}[(x_t - \mu)(x_{t+k} - \mu)]}{\sqrt{\mathbb{E}[(x_t - \mu)^2] \mathbb{E}[(x_{t+k} - \mu)^2]}} = \frac{\mathbb{E}[(x_t - \mu)(x_{t+k} - \mu)]}{\sqrt{\sigma^2_x \sigma^2_{x+k}}}
\]  

(2.14)

In a stationary process, the assumption holds that the process is a specific state of a statistical equilibrium. The stationary assumption implies constant variance, so the variance \( \sigma^2_x \) is the same at time \( t + k \). Thus, if the sequence is stationary, the autocorrelation at lag \( k \) can be rewritten as

\[
\rho_k = \frac{\mathbb{E}[(x_t - \mu)(x_{t+k} - \mu)]}{\mathbb{E}[(x_t - \mu)^2]} = \frac{\gamma_k}{\gamma_0}
\]  

(2.15)

where \( \gamma_k = \text{cov}[x_t, x_{t+k}] = \mathbb{E}[(x_t - \mu)(x_{t+k} - \mu)] \) is the autocovariance at lag \( k \). Thus, the autocorrelation function satisfies the same form of difference equation as autoregressive process defined in Equation 2.3.

\[
\rho_k = \psi_1\rho_{k-1} + \psi_2\rho_{k-2} + ... + \psi_p\rho_{k-p} = \sum_{i=1}^{p} \psi_i\rho_{k-i}
\]  

(2.16)

Intuitively, observations are supposed to have strong autocorrelation at (up to) lag \( p \) (\( q \)) in \( AR(p) \) (\( MV(q) \)), and the autocorrelation should be sharply weakened afterwards. However, in SARMA, autocorrelation should also have strong and continuous seasonal pattern.
Partial Autocorrelation Function (PACF) In the autoregressive process $AR(p)$, it is not clear for us to find an appropriate order $p$ to fit observations. Partial autocorrelation function is an efficient tool to exploit autocorrelation function in terms of $p$. We define $\phi_{pj}$ as the $j$th coefficient in an $AR(p)$ process.

$$\rho_j = \phi_{p1}\rho_{j-1} + \phi_{p2}\rho_{j-2} + \ldots + \phi_{pp}\rho_{j-p} = \sum_{i=1}^{p} \phi_{pi}\rho_{j-i}$$  \hspace{1cm} (2.17)

where the value of $\phi_{pp}$ is called the partial autocorrelation function. In intuition, in $AR(p)$, the value of partial autocorrelation should be nonzero for lag less than or equal to $p$ and zero for lag greater than $p$.

2.2 Support Vector Regression

**SVM** Given data points $x_i \in \mathbb{R}^n$ with binary labels $y_i \in \{1, -1\}, i = 1, \ldots, n$, the support vector machine (SVM) tries to find a hyperplane to classify positive and negative data points. The SVM maps data points from high dimensional space into feature space by $\phi(x)$ and finds the optimal hyperplane by maximizing the margin between two classes. Classic SVM constructs a linear hyperplane but can be extended to nonlinear space by kernel functions.

**SVR** While SVM is designed to solve binary classification problem, SVR tries to estimate a function that can predict future values. Considering a set of labeled data $\{(x_1, y_1), (x_2, y_2), \ldots, (x_t, y_t)\}$, where $x_i \in \mathbb{R}^n$ and $y_i \in \mathbb{R}$, SVR defines a generic regression function to fit them:

$$f(x) = w \ast \phi(x) + b$$  \hspace{1cm} (2.18)

where $\phi(x)$ is a nonlinear transformation from $\mathbb{R}^n$ to feature space. Kernel functions like radial basis function (RBF) can be incorporated into SVR by writing weights $w$ as:

$$w = \sum_{i=1}^{t} (\alpha_i - \alpha_i^*) \phi(x_i)$$  \hspace{1cm} (2.19)

and the generic function can be updated as:

$$f(x) = \sum_{i=1}^{t} (\alpha_i - \alpha_i^*) \phi(x_i) \phi(x) + b$$  \hspace{1cm} (2.20)

$$= \sum_{i=1}^{t} (\alpha_i - \alpha_i^*) k(x_i, x) + b$$
Therefore, the overall optimization problem in SVR can be summarized as:

\[
\min C \sum_{i=1}^{t} L(f(x_i) - y_i) + \frac{1}{2} ||w||^2
\]

s.t. \( \sum_{i=1}^{t} \alpha_i - \alpha_i^* = 0, \alpha_i, \alpha_i^* \in [0, C] \) (2.21)

where \( L(f(x_i) - y_i) \) defines loss function. Further improvement with \( \epsilon \)-insensitive loss function and slack variables \( \zeta_i \) can be applied. In traffic applications, the prediction function can be defined as:

\[
x_{t+t} = f(t, l, x_t, x_{t-1}, ..., x_{t-n})
\]

Wu et al. (2004); Lippi et al. (2013) implement SVR with RBF/linear kernel and demonstrate its feasibility and promising results. However, only data points in a short path at rush hours are used for prediction and evaluation, and in order to simplify the problem, other potential factors like weather, holidays and transportation network topology are not taken into consideration.

### 2.3 Gaussian Process

Gaussian Process is a statistical model for continuous domain that casts prior distribution on functions and treats a function as an infinite long vector of values \( \{f_1, f_2, ...\} \) (see also Bishop (2006); Williams and Rasmussen (2006)). However, in practice, Gaussian Process needs to work in finite space as training set and testing set are both finite and discrete. Gaussian Process has been widely researched in regression and classification problem and its derivations include ARMA and Kalman Filter. Xie et al. (2010) and Zhao and Sun (2016) have explored Gaussian Process in traffic forecasting and shown promising improvement. However, Gaussian Process is not suitable for relatively longer term prediction like more than 1 hour, as the variance can be accumulated to extremely large. A Gaussian Process model can be notated by \( GP(m, k) \), where \( m \) is a mean function and \( k \) is a covariance function. Based on the Bayes theorem, the Gaussian Process can be written as:

\[
p(f|X, y) = \frac{p(y|f, X)p(f)}{p(y|X)}
\]

where \( p(f) = GP(m, k) \) as prior

\( p(y|f, X) = N(f(X), \sigma^2_n I) \) as likelihood

\( p(y|X) = \int p(y|f, X)p(f|X)df \) as evidence

\( p(f|X, y) = GP(m_p, k_p) \) as posterior
In prediction stage, posterior distribution \( p(f_t|X, y, X_t) \) at test point \( X_t \) can be obtained:

\[
p(f_t|X, y, X_t) = \mathcal{N}(\mathbb{E}(f_t|X, y, X_t), \mathbb{V}(f_t|X, y, X_t))
\]

\[
\mathbb{E}(f_t|X, y, X_t) = m_p(X_t) = m(X_t) + k(X_t, X)(K + \sigma_n^2 I)^{-1}(y - m(X)) \tag{2.24}
\]

\[
\mathbb{V}(f_t|X, y, X_t) = k(X_t, X_t) - k(X_t, X)(K + \sigma_n^2 I)^{-1}k(X, X_t)
\]

With a mean function and covariance function, the \( GP(m, k) \) is fully specified. Covariance function leads to different structural patterns such as smoothness and periodicity. Therefore, for traffic prediction problem, proper covariance function would be essential. There are several popular choices of covariance functions:

Gaussian covariance function \( k(x_i, x_j) = \sigma_f^2 \exp(-\frac{(x_i - x_j)^T(x_i - x_j)}{l^2}) \)

Matérn covariance function \( k_{\frac{3}{2}}(x_i, x_j) = \sigma_f^2 (1 + \sqrt{3}\frac{|x_i - x_j|}{l}) \exp(-\sqrt{3}\frac{|x_i - x_j|}{l}) \)

Periodic covariance function \( k(x_i, x_j) = \sigma_f^2 \exp(-\frac{2\sin^2(\omega(x_i - x_j)/2\pi)}{l^2}) \tag{2.25} \)

### 2.4 Deep Learning Models

Deep learning, or Deep Neural Networks (DNNs), was previously known as artificial neural networks (ANNs) and was initially inspired by information communication in biological nervous system (Goodfellow et al. (2016)). Deep learning models are assembled by multiple layers, which include visible layers and hidden layers. Visible layers contain input and output, and hidden layers are designed to extract features by feedforward operations. Rumelhart et al. (1988) introduces back propagation based on gradient to train neural networks. With stronger representation learning capability, increasing dataset sizes and real world challenges, deep learning has rapidly growth in applications. Deep learning models, e.g. multilayer perceptron (MLP), convolutional neural network (CNN), recurrent neural network (RNN), generative adversarial networks (GAN, Goodfellow et al. (2014)), have been widely applied in computer vision (Krizhevsky and Hinton (2009); Radford et al. (2015)), natural language processing(Yu et al. (2017)), audio generation (van den Oord et al. (2016)) and etc. Recent research have also explored LSTM neural network in travel time forecasting (Duan et al. (2016); Ma et al. (2017)) and residual networks in crowd flow prediction (Zhang et al. (2017)).
### 2.4.1 Multilayer Perceptron

Multilayer perceptron, also known as MLP, fully connected network and dense network, is a matrix multiplication operations mapping inputs to outputs and now has been widely applied in decoder networks. A typical MLP is a three-layer neural network, as demonstrated in Figure 2.3. Mathematically, the MLP can be written as:

\[
y = f^{(2)}(W^{(2)}(f^{(1)}(W^{(1)}x + b^{(1)}) + b^{(2)}) + b^{(2)})
\]  

(2.26)

with input \(x\), output \(y\), parameters \(W, b\) and activation function \(f\).

*Figure 2.3:* An example of three-layer MLP.

---

### 2.4.2 Convolutional Neural Networks

Convolutional neural networks, also knows as CNNs, has been widely applied in many areas and has shown outstanding capability in processing grid-like data (LeCun et al. (1989)). Examples include 1-D time series samples with regular time intervals, and images which can be thought as 2-D grid pixels (Goodfellow et al. (2016)). In the mid 20th century, neurophysiologists tried to understand how the brain responds to images and discovered that some neurons in the brains of cats and monkeys are highly sensitive to edges in small regions in visual fields (Hubel and Wiesel (1959, 1962, 1968)). Thus, as a artificial intelligence model, CNNs is fundamentally supported by neuron science. Recent paper Ma et al. (2017) treats traffic data as 2-D images, one dimension of time, one dimension of location, and demonstrates better accuracy with CNNs on the speed prediction (Figure 2.4).

**Convolution Operation** The convolution is designed to scan a sequence \(x\) with a weighting function \(w\). A continuous convolution operation can be written and de-

---

*Source from http://deeplearning.net/tutorial/mlp.html, accessed: 2017-08-24*
**Figure 2.4:** An example of CNNs. The CNNs based framework implemented by Ma et al. (2017) for transportation network speed prediction.

Define as:

\[ s(t) = (x * w)(t) = \int x(a)w(t - a)da \]  \hspace{1cm} (2.27)

In machine learning applications, the input data is discrete and usually multidimensional. Using 2-D images as an example, we can define a 2-D discrete convolution:

\[ S(i, j) = (I * K)(i, j) = \sum_{m} \sum_{n} I(m, n)K(i - m, j - n) \]  \hspace{1cm} (2.28)

where the \( I(m, n) \) refers to the input image, and \( K(m, n) \) is called kernel or feature map. Through visualisation, Yosinski et al. (2015) helps us understand how CNN works. Convolution operations (Figure 2.5) use feature maps to scan images, measure their similarity, and outputs a heatmap \( S(i, j) \) which highlights regions of interest. For example, if a feature map, which is extracted from images without supervision, is a outline of human face, the heatmap \( S(i, j) \) can indicate location of human faces unless there is no faces. The feature maps for raw images can be straightforward, but after several hidden layers, the feature maps can be highly abstract.

**Pooling** Pooling can be seen as a summarization of responses over a whole neighbourhood. Pooling drops useless information by reducing the output size, which helps to make the network invariant to small changes of the input. Max pooling is one of the most popular pooling operations, which reports the maximum value
within a rectangular neighbourhood, as shown in Figure 2.6.

**Figure 2.5:** Convolution operation. The input (blue) is element-wisely multiplied by feature maps (dark blue) and the output (green) is computed by applying the feature maps to the corresponding region of the input. Source from: Dumoulin and Visin (2016).

**Figure 2.6:** Max pooling. The max pooling operation returns the maximum value (dark green) in the rectangular region (dark blue). Source from: Dumoulin and Visin (2016).
2.4.3 Recurrent Neural Network

As illustrated in Figure 2.7, the basic idea of recurrent neural network (RNN) is that an output is produced at each time step and the hidden units are recurrently connected, which means the output $h_t$ depends on both the input $x_t$ and previous information $h_{t-1}$ (see also Goodfellow et al. (2016)). The cell decides how $h_t$ is computed given the sequential data. A simple choice for the cell can be a linear operation which accumulates sequential information and outputs the hidden states.

The chain structure decides that RNN is intimately suitable for sequence data analysis. Therefore, RNN has shown powerful learning capability in machine translation (Sutskever et al. (2014)), text-to-image synthesis (Reed et al. (2016); Dong et al. (2017b)), speech generation (van den Oord et al. (2016)), traffic prediction (Duan et al. (2016); Li et al. (2017)) and many other applications.

Figure 2.7: Recurrent neural network\textsuperscript{a}. A chunk of neural network is integrated in the cell with $x_t$ as input, $h_t$ as output. The cell allows information to be passed from current step to its successor. The left figure shows the basic structure of RNN and an equivalent unfolded version in the right.

\textsuperscript{a}The figure is reproduced from \url{http://colah.github.io/posts/2015-08-Understanding-LSTMs/}, accessed: 2017-08-24

**LSTM** The long short-term memory (LSTM), proposed by Hochreiter and Schmidhuber (1997), based on gated recurrent units, has become a very popular and effective choice for the RNN cell in practical applications. Intuitively, there are cases where we need more context to decide $h_t$. Recent information closely before time step $t$ may be not enough and information further back is necessary. The LSTM introduces a highway to achieve accumulation of information for a long duration and also a forget gate layer to decide whether to drop an old state or not. The key idea is that LSTM can keep or add information to the cell state where is regulated by gates. An illustration of LSTM is shown in Figure 2.8.
2.5. **GLOBAL DATA OBSERVATORY**  

**Figure 2.8:** LSTM\(^{a}\). The diagram illustrates the recurrent connection between LSTM cells. After sigmoid function \(\sigma\), the values will be put into the gates. Previous information will be accumulated into the next step.

---

**2.5 Global Data Observatory**

Global Data Observatory (GDO) \(^1\), largest of its kind in the Europe, built by Data Science Institute at Imperial College London, assembled by 64 monitors and 32 computers, features an enveloping circular screen wall with ultra high resolution (Figure 2.9). GDO provides 313-degree surround vision and friendly interactive system, which leverage powerful visualisation of big data to help analysts extract useful knowledge and make best quantitative decisions.

GDO Software Development Kit (SDK) provides two development modes, Cluster Mode and Section Mode. In the Cluster Mode, all 64 monitors work individually and information for each monitor will be distributed by a central server. The Section Mode splits the screen wall into five sections, as shown in Figure 2.10. Visualisation on each section is implemented based on a web browser and information can be transferred among the sections by connection tools such as Socket.IO \(^2\), PeerJS \(^3\) and SignalR \(^4\). In this project, we finished visualisation of traffic data and evaluation of volume prediction on the Section Mode of GDO, which will be further discussed in Section 5.5.

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\(^a\)The figure is reproduced from http://colah.github.io/posts/2015-08-Understanding-LSTMs/, accessed: 2017-08-24

\(^1\)GDO, see also: https://www.imperial.ac.uk/data-science/data-observatory/, accessed: 2017-09-04

\(^2\)Socket.IO is a real-time tool based on Node.js: https://socket.io/, accessed 2017-08-27.

\(^3\)PeerJS supports peer-to-peer data transfer: http://peerjs.com/, accessed 2017-08-27.

\(^4\)SignalR is a real-time library for ASP.NET: http://signalr.net/, accessed 2017-08-27.
Chapter 2. Background

2.5. GLOBAL DATA OBSERVATORY

**Figure 2.9:** Global Data Observatory in Data Science Institute at Imperial College London.

![Global Data Observatory](https://pbs.twimg.com/media/C4oYInAXUAAMEN.jpg), accessed: 2017-08-25

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**Source from [https://pbs.twimg.com/media/C4oYInAXUAAMEN.jpg](https://pbs.twimg.com/media/C4oYInAXUAAMEN.jpg), accessed: 2017-08-25**

---

**Figure 2.10:** Section Mode of GDO. The screen wall is split into five sections and each section is based on web browser.

![Section Mode of GDO](https://wiki.imperial.ac.uk/display/DG/1+-+Setup)

---

**Source from [https://wiki.imperial.ac.uk/display/DG/1+-+Setup](https://wiki.imperial.ac.uk/display/DG/1+-+Setup), accessed: 2017-08-27, privilege may be needed to view this link.**
Chapter 3

Data Analysis and Refinery

This chapter provides introduction and analysis on the traffic datasets we use. We will introduce discovery on temporal patterns of traffic volume including peak hours, seasonality and special patterns on special days. Additionally, spatial correlations in highway networks will be demonstrated. Moreover, data refinery as prerequisite for proposed models is also essential and will be covered at the end of this chapter.

3.1 Datasets

In this project, we investigate and implement experiments on two traffic datasets, the Highways England dataset and the KDDCUP 2017 dataset. The analysis on temporal and spatial relations in this chapter (Section 3.2 and 3.3) is mainly based on the Highways England dataset, while the KDDCUP 2017 dataset will be used as benchmark in Chapter 5 to demonstrate outstanding performance of our proposed methodologies.

3.1.1 Highways England Dataset

Since 2015, the UK government and Highways England have published traffic data on all motorways and ‘A’ roads regulated by Highways England. The dataset provides average speed, average journey time, traffic flow volume of different types of vehicles for 15-minute periods from January 2006 to June 2017, and it is still updating. There are more than 14,000 monitoring nodes collecting real time traffic data.

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Chapter 3. Data Analysis and Refinery

3.1. DATASETS

data in the entire England region as shown in Figure 3.1. The distribution of nodes is closely compact in suburban area around huge cities like London, Birmingham and Manchester. According to the official introduction of the dataset, the data are collected and estimated from combination of different sources including automatic number plate recognition cameras, in-vehicle GPS and inductive loops in the road surface. Quality index based on number of valid record is provided and can be used to drop unreliable data points.

In this project, as we focus on short-term traffic flow prediction, we select data of traffic volume from 1st January 2016 to 30th June 2017, including 52 nodes around Uxbridge and Heathrow Airport, as shown in Figure 3.1. More information about the nodes can be found in Table 7.1 in Appendices. For simplicity, the nodes are named by simplified numerical ID, e.g. 1017, 2209 and 345. Among the 52 nodes, 46 of them are located on the motorways M4 and M25, and the other 6 nodes are selected from 'A' roads which are closed to entrances or exits of the motorways. There is one and only one data point each 15-minute slice, so 96 data points per day and 672 per week. Each data point provides several fields of information as shown in Table 3.1. Both total carriageway flow and type of days will be applied as inputs (features) to forecast traffic flow in the short-term future. You can find an example of data points in the Table 3.2. We will demonstrate interesting discoveries and analysis based on the Highways England dataset in the following sections of this Chapter.

3.1.2 KDDCUP17 Dataset

KDDCUP 2017 2 released highway tollgate traffic flow prediction challenges with two tasks, which are journey time prediction and traffic volume prediction. As our project focuses on traffic volume prediction, we select the second task and corresponding data as benchmark. The training set provides traffic data (volume, weather, holiday, etc.) from 19th Sep to 17th Oct 2016 with 20-minute intervals. More information can be found in Table 3.3.

Given traffic data during 6-8am and 15-17pm (green slots in Figure 3.2) in the following week, from 18th Oct to 24th Oct 2016, the task is to predict traffic volume during 8-10am and 17-19pm each day in the week (red slots in Figure 3.2) at each tollgate. There are only three tollages in the dataset and they are labelled as 1, 2, 3. In Chapter 5, we will demonstrate our proposed model outperforms state-of-the-art methods in KDDCUP 2017 competition.

---

Table 3.1: Fields of information provided in the Highways England dataset.

<table>
<thead>
<tr>
<th>Fields</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local Time</td>
<td>Local time (British Standard Time) with 15-minute time intervals. Normally, one and only data point for each 15-minute time slice.</td>
</tr>
<tr>
<td>Day Type ID</td>
<td>Days are classified into several categories, and valid ID includes:</td>
</tr>
<tr>
<td></td>
<td>0,1,2,3,4  Monday to Friday (Workdays).</td>
</tr>
<tr>
<td></td>
<td>5,6         Saturday and Sunday (Weekends).</td>
</tr>
<tr>
<td></td>
<td>7,9,11      School holidays but excluding days falling within type 12,13,14.</td>
</tr>
<tr>
<td></td>
<td>12          Bank Holiday.</td>
</tr>
<tr>
<td></td>
<td>13          Christmas period holiday between Christmas Day and New Year’s Day but excluding days falling within type 14.</td>
</tr>
<tr>
<td></td>
<td>14          Christmas Day and New Year’s Day.</td>
</tr>
<tr>
<td>Total Carriageway Flow</td>
<td>The number of vehicles counted on any lane within the 15-minute time window.</td>
</tr>
<tr>
<td>Quality Index</td>
<td>The indication of quality of data collected. The number of valid 1-minute record within the 15-minute time window. 0 indicates no valid record in the time window and 15 indicates the best quality.</td>
</tr>
</tbody>
</table>
Table 3.2: An example of data points at Node 1017 in the Highways England dataset. In this example, the data points are collected on Friday morning with good quality. The local time has 15-minute time intervals and total carriageway flow is the number of vehicles that go through Node 1017 in corresponding time slice.

<table>
<thead>
<tr>
<th>Local Time</th>
<th>Day Type ID</th>
<th>Total Carriageway Flow</th>
<th>Quality Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>01/07/2016 08:14:00</td>
<td>4</td>
<td>1107</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 08:29:00</td>
<td>4</td>
<td>1104</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 08:44:00</td>
<td>4</td>
<td>1015</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 08:59:00</td>
<td>4</td>
<td>966</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 09:14:00</td>
<td>4</td>
<td>913</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 09:29:00</td>
<td>4</td>
<td>932</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 09:44:00</td>
<td>4</td>
<td>1030</td>
<td>15</td>
</tr>
<tr>
<td>01/07/2016 09:59:00</td>
<td>4</td>
<td>901</td>
<td>15</td>
</tr>
</tbody>
</table>

Figure 3.1: Highways England dataset. (a) The left figure shows distribution of monitoring nodes in England region. The nodes are closely compacted around cities like London, Birmingham and Manchester. (b) The right figure shows the selected 52 nodes around Uxbridge and Heathrow Airport. The nodes are mainly distributed on motorways M4 and M25, and 'A' roads closed to their entrances or exits. More information about the selected nodes can be found in Table 7.1.

\(^a\)Source from http://webtris.highwaysengland.co.uk/, accessed: 2017-08-23
Figure 3.2: Time windows for traffic volume prediction in KDDCUP 2017 dataset.

Table 3.3: Fields of information provided in the KDDCUP 17 dataset.

<table>
<thead>
<tr>
<th>Fields</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>The time when a vehicle goes through the tollgate.</td>
</tr>
<tr>
<td>Tollgate ID</td>
<td>ID of the tollgate, which can be 1, 2 or 3. There are only three tollgates.</td>
</tr>
<tr>
<td>Holiday</td>
<td>0: normal, or 1: public holidays.</td>
</tr>
<tr>
<td>Air Pressure</td>
<td>Air pressure (hPa: Hundred Pa).</td>
</tr>
<tr>
<td>Wind Speed</td>
<td>Wind speed (m/s).</td>
</tr>
<tr>
<td>Temperature</td>
<td>Temperature (°C).</td>
</tr>
<tr>
<td>Precipitation</td>
<td>Precipitation (mm).</td>
</tr>
</tbody>
</table>

Source from https://tianchi.aliyun.com/competition/information.htm?raceId=231597, accessed: 2017-08-23
3.2 Temporal Pattern

Compared with minor roads in urban area, the highways have fewer entrances and exits per unit distance, fewer traffic lights that can block vehicles, higher average speed and higher traffic volume. Visualisation of traffic volume indicates strong daily pattern like peak hours, and strong continuous seasonality by autocorrelation. Furthermore, special days e.g. weekends and Christmas holidays have significantly different traffic pattern with workdays.

3.2.1 Peak Hours

Statistics based on traffic data of 52 nodes from 1st January 2016 to 30th June 2017 show there are on average 744.12 vehicles per 15 minutes on motorways (M4 and M25), with maximum 2512 during peak hours, and average 255.51 vehicles per 15 minutes on 'A' roads, with maximum 773 (Table 3.4). The traffic volume during weekends is lower than workdays and usually has only one peak in most nodes but there are some exceptions.

During workdays, the peak hours start 07:00-08:00 in the morning and ends 19:00-20:00 in the evening. As illustrated in the Figure 3.3, the morning peak is usually higher and lasts shorter than the evening peak during workdays, which may be explained by intuition that most people drive for work crowded in a short period of time early in the morning, but the time for going home is diverse and lasts longer.

In addition, we can find symmetry in pairs of nodes. For example, Figure 3.4 demonstrates that Node 7044-1 has higher morning peak but, on the contrary, Node 7045-1 has higher evening peak. On the map, we can easily find that Node 7044-1 heads towards Heathrow Airport while Node 7045-1 heads for the opposite direction to M25. Such symmetry may help us unearth potential moving pattern of people in a small local area.

Moreover, dramatic decreasing of traffic volume in a short time window as demonstrated in Figure 3.5 attract our attention, which may be caused by abnormal conditions including unexpected accidents and planned events, but such record is unavailable in the dataset. Though the traffic volume has overall strong recurrent pattern, interference of variance and those abnormal outliers can be challenging for our models.
### 3.2. TEMPORAL PATTERN

**Table 3.4:** Statistics on number of vehicles per 15 minutes. The traffic volume on motorways (M4 and M25) is much higher than that on 'A' roads.

<table>
<thead>
<tr>
<th></th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motorways</td>
<td>2512</td>
<td>0</td>
<td>774.12</td>
<td>732.00</td>
</tr>
<tr>
<td>'A' Roads</td>
<td>773</td>
<td>0</td>
<td>225.51</td>
<td>214.00</td>
</tr>
</tbody>
</table>

**Figure 3.3:** Traffic volume from 6th Feb 2017 (Monday) to 12th Feb 2017 (Sunday) at Node 496, 1017 and 5146. During workdays, the morning peak usually has higher traffic volume and lasts shorter than the evening counterpart, which may be explained by intuition that people drive towards work crowded in a short time window in early morning but the time for going home is very different. However, such pattern does not hold on weekends.

#### 3.2.2 Seasonality and ARMA Order

Intuitively, traffic volume should have continuous daily or weekly pattern. For example, during workdays, given a specific location, traffic volume should be similar with that one day before. Weekends are different from workdays but similarity between this and previous weekend is not easy to be ignored. The seasonality is a fundamental assumption in short-term traffic prediction problems and the models we use, not
Chapter 3. Data Analysis and Refinery

3.2. TEMPORAL PATTERN

Figure 3.4: Symmetry between Node 7044-1 and 7045-1. On workdays, the traffic volume during morning peak of Node 7044-1 is significantly higher than evening peak. However, the Node 7045-1 has an opposite traffic pattern. On the map, both Node 7044-1 and 7045-1 are located on road A3113, while 7044-1 heads towards Heathrow Airport but 7045-1 towards the opposite direction to motorway M25. Such symmetry may unearth moving behaviour of people in the small area.

Figure 3.5: Abnormal conditions at Node 866 and 3931. The green background highlight outliers. The dramatic decreasing of traffic volume may be caused by accidents or maintenance events but such record is not available in our dataset.

Figure 3.6 illustrates that daily seasonality is strong and consistent at Node 2291, 5146 and 6157-1, and the results of PACF indicates that an appropriate order for ARMA is 1. In fact, such conclusions hold for all 52 nodes. As mentioned in Section 3.1, the number of lags for each day is 96. Therefore, the value at a specific time is positively correlated with neighbouring values and those days before, while negatively correlated with those half days in advance. Moreover, Figure 3.7 demonstrates special cases at Node 7044-1 and 7045-1, and such pattern is caused by the special symmetry between Node 7044-1 and 7045-1 and the asymmetry between morning and evening peak as shown in Figure 3.4.

only SARIMA and also neural networks. Autocorrelation function (ACF), which are introduced in Section 2.1.4, can help us find out the order of seasonality. Besides, we also explore partial autocorrelation function (PACF), which is created to decide order of ARMA, at each node.

Figure 3.6 illustrates that daily seasonality is strong and consistent at Node 2291, 5146 and 6157-1, and the results of PACF indicates that an appropriate order for ARMA is 1. In fact, such conclusions hold for all 52 nodes. As mentioned in Section 3.1, the number of lags for each day is 96. Therefore, the value at a specific time is positively correlated with neighbouring values and those days before, while negatively correlated with those half days in advance. Moreover, Figure 3.7 demonstrates special cases at Node 7044-1 and 7045-1, and such pattern is caused by the special symmetry between Node 7044-1 and 7045-1 and the asymmetry between morning and evening peak as shown in Figure 3.4.
Figure 3.6: Autocorrelation function (ACF) and partial autocorrelation function (PACF) at Node 2291, 5146 and 6157-1. The three figures on the top computed by ACF show strong and consistent daily seasonality. Results of PACF at the bottom find that an appropriate order for ARMA is 1. Such conclusions hold for all 52 nodes.

Figure 3.7: Special cases of autocorrelation function (ACF) and partial autocorrelation function (PACF) at Node 7044-1 and 7045-1. Such pattern is caused by the special symmetry between Node 7044-1 and 7045-1 and the asymmetry between morning and evening peak as shown in Figure 3.4.
Chapter 3. Data Analysis and Refinery 3.2. TEMPORAL PATTERN

3.2.3 Special Days

In the previous sections, we have analysed typical temporal patterns in traffic, and such patterns hold strong and consistent on most days. However, there are some special days that the series may behave differently. The Highways England dataset provides indication of type of days as showed in Table 3.1. There are six types of special days including weekends, school holidays, bank holidays, Christmas Day, Christmas period and New Year’s Day. We firstly introduce some measurements to help us find difference between workdays and special days.

1. Peak hours: The moments have highest 25% traffic volume.
2. Start of peak hours: The earliest moment each day of peak hours.
3. End of peak hours: The latest moment each day of peak hours.
4. Percentage difference of all hours:

\[
\frac{\text{mean}(x_t \mid t \in T_{\text{workdays}}) - \text{mean}(x_t \mid t \in T_{\text{specialdays}})}{\text{mean}(x_t \mid t \in T_{\text{workdays}})}
\]  
(3.1)

where \(T_{\text{workdays}}\) is a set of all hours on workdays, \(T_{\text{specialdays}}\) is a set of all hours on special days.

5. Percentage difference of peak hours:

\[
\frac{\text{mean}(x_t \mid t \in T_{\text{peakworkdays}}) - \text{mean}(x_t \mid t \in T_{\text{peakspecialdays}})}{\text{mean}(x_t \mid t \in T_{\text{peakworkdays}})}
\]  
(3.2)

where \(T_{\text{peakworkdays}}\) is a set of peak hours on workdays, \(T_{\text{peakspecialdays}}\) is a set of peak hours on special days.

Weekends: On the 52 nodes, compared with workdays, traffic on weekends has 10.9% lower volume on average. And during peak hours, the traffic volume on weekends is 9.3% lower than workdays. Besides, the average start of peak hours is postponed from 07:38am on workdays to 11:03am on weekends, and the average end of peak hours is also delayed from 19:28 on workdays to 19:56 on weekends. Usually, there are two peaks during workdays (morning peak and evening peak), but such pattern does not hold on weekends. Figure 3.8 and Table 3.5 compare traffic volume between workdays and weekends.

Bank Holidays: Bank holidays have similar traffic pattern as weekends, which is easily to understand as Bank holidays are Mondays following weekends. On average, the bank holidays have 14.8% less traffic (all hours) and 11.4% less in peak hours. Additionally, the start of peak hours is further postponed to 11:24am while the end of peak hours is 19:47 about 20 minutes later than workdays. Figure 3.9 and Table 3.6 illustrate differences between bank holidays and workdays.
School Holidays: The traffic volume during school holidays does not have obvious difference with workdays. Figure 3.10 and Table 3.7 demonstrate that the average percentage difference between workdays and school holidays is about \( \pm 1\% \), which can be ignored. Therefore, we can make a conclusion that school holidays do not have significant impact on highway traffic.

Christmas Period: Christmas period refers to the days after Christmas Day and before New Year’s Day (26th Dec to 30th Dec). In our dataset, we have only one Christmas period which is in 2016. Figure 3.11 and Table 3.8 show that Christmas period has overall 20.0\% less traffic and 14.6\% less in peak hours than workdays. The start of peak hours is delayed to 11:26am on average, but 24 minutes earlier ending of peak hours in the evening, which is 19:05.

Christmas Day: In our dataset, there is only one Christmas Day which is on 25th Dec 2016. Considering all 52 nodes, Christmas Day has significantly lower traffic volume than workdays. Figure 3.12 and Table 3.9 indicate that 45.1\% fewer vehicles would drive on the highways than workdays. The highest volume on the Christmas Day is around the borderline of peak hours on workdays. In addition, the start of peak hours is 10:59am which is similar with that on weekends. However, the ending of peak hours is rather late in the evening about 20:48.

New Year’s Day: The dataset includes New Year’s Days of 2016 and 2017 which have overall 35.1\% less traffic than workdays. Interestingly, there are unique midnight peaks on New Year’s Days as highlighted in the left column of Figure 3.13. The midnight peak has relatively higher volume on the roads outwards central London which indicates crowded of people going out of the city after midnight celebration events. Moreover, the start of peak hours is also significantly delayed to 12:32, which is nearly 5 hours later than workdays. Further comparison can be found in Figure 3.13 and Table 3.10.

Table 3.5: Comparison between workdays and weekends on all 52 nodes. The percentage differences are defined by Equation 3.1 and 3.2. As shown, workdays have about 10\% higher traffic volume and earlier start/end of peak hours than weekends.

<table>
<thead>
<tr>
<th></th>
<th>Max</th>
<th>Min</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage difference (all hours)</td>
<td>0.4105</td>
<td>0.0226</td>
<td>0.1087</td>
</tr>
<tr>
<td>Percentage difference (peak hours)</td>
<td>0.4854</td>
<td>-0.0278</td>
<td>0.0927</td>
</tr>
<tr>
<td>Start Peak Hours (Workdays)</td>
<td>09:14</td>
<td>06:42</td>
<td>07:38</td>
</tr>
<tr>
<td>Start Peak Hours (Weekends)</td>
<td>12:39</td>
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</tr>
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<td>End Peak Hours (Workdays)</td>
<td>21:36</td>
<td>16:02</td>
<td>19:28</td>
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<tr>
<td>End Peak Hours (Weekends)</td>
<td>21:03</td>
<td>18:11</td>
<td>19:56</td>
</tr>
</tbody>
</table>
Figure 3.8: (Top) Weekends v.s. workdays at Node 279 and 5246. The green background highlights traffic volume on weekends. The red and orange lines indicate borderline of peak hours (highest 25% volume) on workdays and weekends respectively. As shown, weekends have lower traffic volume than workdays. (Middle) Histogram of percentage difference on all 52 nodes. The two figures in the middle indicate the traffic volume is on average 10% higher during workdays than weekends. (Bottom) Histogram of start/end of peak hours on all 52 nodes. The two figures at the bottom illustrate the change of average start/end of peak hours on weekends. The delay of average start of peak hours on weekends is about three and half hours which is clearly demonstrated on the bottom left histogram. The average end of peak hours is postponed about half an hour.
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Chapter 3. Data Analysis and Refinery

Figure 3.9: (Left) Workdays v.s. bank holidays at Node 279 and 5245. (Middle) Histogram of percentage difference on all 52 nodes. (Right) Histogram of start/end of peak hours on all 52 nodes. There is significant delay of start of peak hours and lower traffic volume compared with workdays.

Table 3.6: Comparison between workdays and bank holidays on all 52 nodes. The traffic patterns on bank holidays are similar with weekends as shown in Table 3.5. Workdays have on average 14.76% higher traffic volume than bank holidays.

<table>
<thead>
<tr>
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<tbody>
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<td>0.4547</td>
<td>0.0258</td>
<td>0.1476</td>
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<td>Percentage difference (peak hours)</td>
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<td>-0.0519</td>
<td>0.1149</td>
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<td>09:14</td>
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<tr>
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<td>12:47</td>
<td>06:55</td>
<td>11:24</td>
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<td>21:36</td>
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<td>19:28</td>
</tr>
<tr>
<td>End Peak Hours (Bank Holidays)</td>
<td>22:05</td>
<td>17:51</td>
<td>19:47</td>
</tr>
</tbody>
</table>
Figure 3.10: (Left) Workdays v.s. school holidays at Node 279 and 5245. (Middle) Histogram of percentage difference on all 52 nodes. (Right) Histogram of start/end of peak hours on all 52 nodes. As shown, there is no much difference between workdays and school holidays.

Table 3.7: Comparison between workdays and school holidays on all 52 nodes. There is no much difference between workdays and school holidays.

<table>
<thead>
<tr>
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<td>-0.0349</td>
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<td>Percentage difference (peak hours)</td>
<td>0.0620</td>
<td>-0.0130</td>
<td>0.0102</td>
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<td>Start Peak Hours (Workdays)</td>
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<td>Start Peak Hours (School Holidays)</td>
<td>10:55</td>
<td>06:48</td>
<td>07:44</td>
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<td>End Peak Hours (Workdays)</td>
<td>21:36</td>
<td>16:02</td>
<td>19:28</td>
</tr>
<tr>
<td>End Peak Hours (School Holidays)</td>
<td>21:19</td>
<td>14:34</td>
<td>19:17</td>
</tr>
</tbody>
</table>
3.2. TEMPORAL PATTERN

Figure 3.11: (Left) Workdays v.s. Christmas period at Node 2933 and 3031. (Middle) Histogram of percentage difference on all 52 nodes, which indicates busier traffic during workdays. (Right) Histogram of start/end of peak hours on all 52 nodes. As shown, the Christmas period has much later start of peak hours but earlier ending of peak hours.

Table 3.8: Comparison between workdays and Christmas period on all 52 nodes. The Christmas period on average has an overall 20% less traffic and 14% less in peak hours than workdays. The average start of peak hours is further delayed to 11:26, which is nearly 4 hours later than workdays. However, the Christmas period has 24 minutes earlier ending of peak hours.

<table>
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</thead>
<tbody>
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<td>0.0955</td>
<td>0.2002</td>
</tr>
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<td>Percentage difference (peak hours)</td>
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<td>0.1458</td>
</tr>
<tr>
<td>Start Peak Hours (Workdays)</td>
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<td>07:38</td>
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<tr>
<td>Start Peak Hours (Christmas period)</td>
<td>12:42</td>
<td>07:34</td>
<td>11:26</td>
</tr>
<tr>
<td>End Peak Hours (Workdays)</td>
<td>21:36</td>
<td>16:02</td>
<td>19:28</td>
</tr>
<tr>
<td>End Peak Hours (Christmas period)</td>
<td>20:24</td>
<td>17:57</td>
<td>19:05</td>
</tr>
</tbody>
</table>
Figure 3.12: (Left) Workdays vs. Christmas Day at Node 2933 and 3031. The highest volume on the Christmas Day is around the borderline of peak hours during workdays. (Middle) Histogram of percentage difference on all 52 nodes, which indicates significantly lower traffic on the Christmas Day. (Right) Histogram of start/end of peak hours on all 52 nodes. As shown, the Christmas Day has later start/end of peak hours.

Table 3.9: Comparison between workdays and Christmas Day on 52 nodes. Christmas Day has significantly less traffic (45.06%) and later ending of peak hours than workdays.
3.2. TEMPORAL PATTERN

Figure 3.13: (Left) Workdays v.s. New Year’s Day at Node 2243 and 2598. Interestingly, there are midnight peak highlighted by green background. The minor peak is higher at Node 2598 than 2243, because the former node heads outwards central London while the latter one heads the opposite direction. (Middle) Histogram of percentage difference on all 52 nodes, which indicates lower traffic on the New Year’s Day. (Right) Histogram of start/end of peak hours on all 52 nodes. As shown, the New Year’s Day has significantly later start of peak hours around 12:30.

Table 3.10: Comparison between workdays and New Year’s Day on all 52 nodes. New Year’s Day has less traffic (35.14%) and rather later start of peak hours (nearly 5 hours) than workdays.

<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
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<td>0.1824</td>
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<tr>
<td>Percentage difference (peak hours)</td>
<td>0.6538</td>
<td>0.1450</td>
<td>0.2795</td>
</tr>
<tr>
<td>Start Peak Hours (Workdays)</td>
<td>09:14</td>
<td>06:42</td>
<td>07:38</td>
</tr>
<tr>
<td>Start Peak Hours (New Year’s Day)</td>
<td>13:37</td>
<td>06:44</td>
<td>12:32</td>
</tr>
<tr>
<td>End Peak Hours (Workdays)</td>
<td>21:36</td>
<td>16:02</td>
<td>19:28</td>
</tr>
<tr>
<td>End Peak Hours (New Year’s Day)</td>
<td>22:44</td>
<td>17:59</td>
<td>19:16</td>
</tr>
</tbody>
</table>
3.3 Spatial Correlation

Traffic volume at any time and location is correlated with not only previous observations and also observations on neighbouring places. Intuitively, in some busy routes, if a huge volume is observed at the entrances, the locations afterwards should expect and get ready for the volume soon. In the Highways England dataset, the 52 nodes, potentially correlated with each other, are located around Heathrow Airport, one of the busiest airports worldwide.

Figure 3.14 illustrates the correlation coefficient matrix computed by VAR, one of the baselines. Some nodes have strong correlation with each other e.g. Node 1138, 1400 and 1449. However, some nodes on 'A' roads e.g. 6156-1, 6178-1 and 7044-1 have no clear spatial correlation with any others. In the following paragraphs of this section, we will discuss such spatial correlation in specific circumstances.

**Same Direction** Evidences indicate that nodes on the same direction of the same motorway have strong correlation. In Figure 3.15, we select five nodes on M4 westbound (Node 2598, 1449, 1138, 1400, 1017) and four nodes on M25 southbound (Node 5211, 496, 3031, 5399). Though the number of vehicles are different among nodes, the overall trend is highly correlated. We can notice the rise or drop of traffic volume happens with short delay or even simultaneously, which can be helpful for forecasting.

**Opposite Direction** Figure 3.16 selects four nodes on M4, two eastbound and two westbound. As depicted, both directions have similar peak hours, but the traffic eastbound has no direct impact on that westbound and vice versa. During the dramatic drop of traffic westbound, which might be caused by accidents, the traffic eastbound was not affected much. Therefore, the information from opposite direction for traffic prediction can be very limited.

**Crossroads** Circumstances on crossroads need to be discussed case by case. Firstly, we select nodes around the overpass in the northwest of Heathrow Airport, which is the intersection between M4 and M25. Additionally, the large roundabout in the north of Heathrow Airport on M4 is also a good case.

1. One inwards multiple outwards. We select Node 3931 as input and three outwards nodes (Node 5211, 4121, 2291). Node 3931 and 5211 are both located on M25 southbound, while Node 4121 heads westbound and 2291 eastbound on M4. The top three figures in Figure 3.17 have shown that severe change of traffic volume on the input node does affect that on all the three outputs but the influence at Node 5211 is more significant. In most of the times, Node 3931 has no dominant impact at Node 4121 and 2291, but Node 5211 is clearly correlated with Node 3931.

2. Multiple inwards one outwards. Node 3931, 1017, 121 are chosen as inputs and Node 3031 as outputs. Both Node 3931 and 3031 are located both on M25...
southbound, while Node 1017 heads westbound and Node 121 eastbound on M4. The three figures in the middle of Figure 3.17 have shown that the output has highest traffic volume in most of the times and is directly affect by Node 3931. Minor noises at Node 1017 and 121 do not affect Node 3031 much. Moreover, traffic at Node 3031 dropped significantly on the Christmas Eve, as Node 3931 was severely blocked.

(3) Roundabout north of Heathrow Airport. We select Node 1138, 1017, 6156-1 and 6157-1 around the large roundabout. As shown in the map (bottom right of Figure 3.17), traffic flow from Node 1138 can go either straight to Node 1017 or left turn to Node 6157; and vehicles counted by Node 1017 come from either Node 1138 or Node 6156-1. The figures at the bottom of Figure 3.17 illustrate that most vehicles from Node 1138 head toward straight to Node 1017 on workdays, but during Christmas holidays, a large ratio of vehicles from Node 1138 turn left onto Node 6157-1 towards Heathrow Airport in the morning.

**Figure 3.14:** Spatial correlation matrix. It is a symmetric matrix whose diagonal values are higher than those off-diagonal. Some nodes e.g. Node 1138, 1400 and 1449 have significant correlation with one another, while other nodes e.g. 6156-1, 6178-1 and 7044-1 have no clear correlation with any others.

---

3Data of traffic going/coming from north is not available thus not taken into consideration. The conclusions following neither relies on the traffic from/to north.
Figure 3.15: Spatial correlation with same direction. (Top) Traffic volume of five nodes on M4 westbound (Node 2598, 1449, 1138, 1400, 1017). We can notice significant decreasing of traffic and midnight peak on New Year’s Eve happened almost simultaneously. (Bottom) Traffic volume of four nodes on M25 southbound (Node 5211, 496, 3031, 5399). Similar traffic trend on M25 can be found and such correlations stand on both workdays and special days.

Figure 3.16: Spatial correlation with opposite directions. Two nodes westbound (Node 1449, 1138) and two nodes eastbound (Node 2806, 3470) are selected. Though nodes with on the same side have strong traffic similarity, correlation between opposite directions is not significant.
Figure 3.17: Spatial correlation on crossroads. (Top) One inwards (Node 3931) and three outwards (Node 5211, 4121, 2291). The input has direct and dominant influence at Node 5211 which shares the same direction. Node 4121 (left turn) and 2291 (right turn) can be affected if the input traffic volume is severely blocked. (Middle) Multiple inwards (Node 3931, 1017, 121) and one outwards (Node 3031). Node 3031 has the highest volume mostly and is directly affect by Node 3931. Minor noises at Node 1017 and 121 do not affect Node 3031 much but significant changes at Node 3931 can influence all of them. (Bottom) Roundabout around Node 1138, 1017, 6156-1 and 6157-1. On workdays, most vehicles from Node 1138 head straight to Node 1017. However, during Christmas holidays, a large ratio of vehicles from Node 1138 turn left onto Node 6157-1 towards Heathrow Airport in the morning.
3.4 Data Refinery

With combination of multiple sources of raw data collection, the Highways England dataset achieves overall outstanding quality. However, outliers and error points are still inevitable. Besides, in order to make models training easier and quicker, it is necessary to prepare a cleaner and more compact dataset. In this section, we will introduce basic steps we followed in data refinery, which is implemented based on Pandas.

Deduplication In data deduplication, we eliminate duplicate copies of repeating data points. In the Highway England dataset, traffic data is sampled for each 15 minutes, which means there is supposed to be one and only one data point in each 15-minute time slice. Thus, data points are firstly grouped into each corresponding slice. Then for those groups that have multiple data points, we merge the data points into one with average values.

Validation Many reasons such as unexpected accidents, planned maintenance events or breaking down of sensors can result in invalid data points. If there are too many not-a-number or missing values (more than 10%) in a single day, we will drop all data points on that day, which is thought to be unreliable and unsuitable for models. Other invalid or missing data points are filled by interpolation.

Clipping Traffic has lowest volume in midnight during which there can be 10 vehicles per 15 minutes or even fewer in some 'A' roads. Such conditions can be a disaster for models, because 5-vehicle prediction error can lead to more than 50% error rate. Therefore, for better regularisation, we set a lower bound which is the lowest 2% and all values below the lower bound are replaced by the bound value.

Feature Selection The KDDCUP17 dataset provides several factors for traffic prediction, but not all of them have clear correlation with traffic volume. Based on the holiday information provided, we firstly group the dates into three categories, workdays, weekends and public holidays. We finally select traffic volume, type of days, precipitation as features for prediction.

---

Chapter 4

Methodology and Implementation

This chapter will firstly give a formal definition of short-term traffic prediction and analyse limitations of the baselines. We will secondly propose two deep learning models, CNN-LSTM with attention mechanism (CNN-LSTM-Attn) and Temporal-Spatial-LSTM (TS-LSTM). The CNN-LSTM-Attn combines LSTM with CNN embedding and incorporates global attention mechanism to model temporal dependencies. The second model TS-LSTM is built upon CNN-LSTM-Attn but utilises a relational module for spatial dependencies. We will finally introduce the implementation and design pattern of this project which make agile development and efficient model training feasible.

4.1 Short-Term Traffic Prediction

In general, given a sequence of observations \( \{x_1, x_2, \ldots, x_t\} \) at a given location, modeling temporal relations only with model \( \mathcal{M} \) and its parameters \( \theta \), the goal is to predict observations in the near future \( \{x_{t+1}, x_{t+2}, \ldots, x_{t+H}\} \), which can be mathematically defined as:

\[
\hat{x}_{t+1}, \hat{x}_{t+2}, \ldots, \hat{x}_{t+H} = \arg \max_{x_{t+1}, x_{t+2}, \ldots, x_{t+H}} P(x_{t+1}, x_{t+2}, \ldots, x_{t+H} | x_1, x_2, \ldots, x_t; \mathcal{M}; \theta) \tag{4.1}
\]

Considering spatial correlation, we can further define a \( K \times T \) matrix \( \{X_1, X_2, \ldots, X_T\} \) which include observations at \( K \) nodes. The traffic prediction problem with both
4.2 Limitation of Baselines

In the Highways England dataset, four traditional models are chosen as baselines, including SARIMA, VAR, Gaussian Process and Support Vector Regression. Previous literature have demonstrated their performance on traffic prediction tasks, but their limitation is also obvious.

**SARIMA** SARIMA integrates daily seasonality with autoregressive and moving average, which models the repeating daily pattern effectively and efficiently. (1) However, firstly, SARIMA with daily seasonality is insensitive to special conditions such as special days. Special conditions are not taken into consideration mathematically in SARIMA, so the traffic volume predicted on special days is almost same as workdays, which leads to high error rate. (2) In addition, not only on special days, traffic may have minor variance during workdays, but SARIMA cannot react to such variance properly. (3) Thirdly, SARIMA is not a general model, which means a SARIMA trained by a given sequence (at location A) cannot be applied on another sequence (at location B), if the two sequences are different. In the Highways England dataset, unless the two locations are very closed to each other on the same direction of the same road, the two traffic sequences at the two locations respectively are different with each other in most cases. Therefore, as we have 52 nodes in the Highways England dataset, 52 SARIMA models are needed.

**VAR** In the baselines, VAR is the only model that takes correlation among nodes into consideration. VAR performs well in very short-term forecasting (lag 1 or 15 minutes), but lacks stability and accuracy in longer prediction. Without moving average, the predicted sequence has higher variance and can be easily affected by minor noises of previous observations. Additionally, VAR is not sufficiently robust, as outliers in the whole transportation network can also influence prediction significantly.
**Gaussian Process (GP)** Firstly, Gaussian Process can approximate interpolation of given data points with good accuracy and high confidence, but the variance may go outrage as shown in Figure 4.1 if we want to predict observations further right. Secondly, inevitable minor noises make traffic observations look zigzag, which makes it difficult to choose proper kernels and may lead to overfitting.

**Figure 4.1:** The variance of Gaussian Process may go outrage on the right.

---

**Support Vector Regression (SVR)** has similar limitations as the above three baseline models. Performance of SVR relies on choice of kernels. RBF has been proved with outstanding performance in previous literature, but RBF may easily result in overfitting if the sequence is not smooth enough. The linear kernel is more stable for very short-term prediction but fails to achieve satisfying accuracy in longer forecasting.

Experimental support of these arguments and quantitative comparison between baselines and our proposed methodologies will be covered in details in Section 5.3.

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**4.3 Temporal Dependencies**

An essential and fundamental assumption that lead to feasibility of short-term traffic prediction is the consistent seasonality and strong temporal patterns. RNN is born to process sequential data and designed to encode accumulated observations. With leverage of LSTM, RNN is able to connect relative information between data points with a large gap and handle long-term dependencies.

RNN with LSTM has been widely applied in natural language processing. However,
compared with text applications, which have a sequence length of tens or 250 at most (Karpathy et al. (2015); Sutskever et al. (2011); Yu et al. (2017)), traffic prediction have rather longer sequential observations. With 15-minute intervals in the Highways England dataset, there are 96 observations a day and 672 a week. Both intuition and experiments make us believe that more previous observations (longer input sequence) can make the forecasting more robust if modelling properly, while on the other hand, prediction is prone to bias in previous data points with short observations.

Therefore, we propose **CNN-LSTM-Attn** model, which applies CNN for long sequence embedding and global attention mechanism for seasonality. We claim that CNN-LSTM-Attn is capable to leverage both longer observations and consistent seasonal dependencies for traffic volume prediction. Figure 4.2 demonstrates the network structure of CNN-LSTM-Attn.

**Reshaping Input** The model uses one-week observations as input which is reshaped into image-like matrix. The new shape of the input is (7, 96, 2), which refers to 7 days a week, 96 data points a day, and 2 features each point (traffic flow + type of the day).

**CNN** A 2-layer 2D CNN with ReLU and max pooling is applied to reduce the length of sequence and extract more features as representation. CNN is able to capture patterns in local region and processed sequence is then fed into the RNN with LSTM.

**Global Attention** Normally, the target hidden state $h_t$ would be given to the FC decoder directly for outputs. However, the seasonality has shown that short-term prediction is highly related with observations at the same time days before. For example, prediction at 8-10am should be similar with previous observations at 8-10am but has trivial relations with traffic in midnight. Thus, we introduce global attention mechanism proposed by Luong et al. (2015) which considers all source hidden states of the RNN and derive an attentional hidden state $\hat{h}_t$.

The alignment vector $\alpha_t$ is defined to measure relations between each source hidden state $h_s$ and the target hidden state $h_t$.

$$\alpha_t(s) = \text{softmax}(h_s, h_t) = \frac{\exp(\text{score}(h_s, h_t))}{\sum_{s'} \exp(\text{score}(h_{s'}, h_t))}$$  \hspace{1cm} (4.3)

where score is a content-based linear function which is defined as:

$$\text{score}(h_s, h_t) = h_s^T W_\alpha h_t$$  \hspace{1cm} (4.4)

The alignment vector $\alpha_t$ will then be used to derive a context vector $c_t$, which is
4.3. TEMPORAL DEPENDENCIES  Chapter 4. Methodology and Implementation

a weighted linear combination of all source hidden states and their corresponding alignment vectors.

\[ c_t = \sum_s \alpha_t(s)h_s \]  \hspace{1cm} (4.5)

The attentional hidden state \( \hat{h}_t \) is the concatenation of \( c_t \) and \( h_t \), and will be transmitted to the FC decoder.

**FC Decoder** The decoder is composed of dropout and fully connected hidden layers. The dropout is applied as an efficient regularisation to prevent overfitting (Srivastava et al. (2014)). The decoder has eight outputs which are the predicted values of eight observations in the next 2 hours. The eight values are predicted at the same rather than one by one, because we believe that all information needed to predict future values is inside the input observations. If the representation learned by CNN-LSTM-Attn is good enough, the decoder should be able to forecast with good accuracy. As the next 2-hour values are predicted together, there is no need to deal with accumulation of mistakes (Pascanu et al. (2013)).

The structural settings of CNN-LSTM-Attn, such as 1D or 2D CNN, and number of units in the FC decoder, rely on the size of input sequence and vary if we use one-day rather than one-week observations as input. But the idea and overall structure of CNN-LSTM-Attn remain the same and can potentially be applied to other sequential data.

**Figure 4.2:** CNN-LSTM-Attn network structure. The CNN-LSTM-Attn consists of four sub-networks, CNN, RNN with LSTM, global attention mechanism and fully connected decoder.
4.4 Spatial Dependencies

Temporal dependencies provide fundamental clues for short-term traffic prediction, and spatial dependencies can do the same. Section 3.3 has demonstrated clear spatial correlation among nodes, especially nodes with same direction and those around crossroads. Therefore, modelling and encoding spatial dependencies among nodes could be useful for prediction.

Santoro et al. (2017) proposes a simple module for relational reasoning in CNN. In the visual question answering scenario, the relational module works together with CNN and RNN to combine information from images and text, and understand relation between objects. For example, given an image of 3D-rendered objects, the deep neural network with relational module is able to answer whether there are any rubber objects that have same size as the yellow metallic cylinder. The relational module is composed of two separated FC networks and considers relations across all pairs of objects, which are extracted by CNN.

Besides, Li et al. (2017) introduces an spatial attention mechanism in RNN. The idea is to use a content-based function to measure relations between two nodes and derive an spatial attentional hidden state which is a weighted combination of target hidden states of all nodes.

Based on the relational module and the spatial attention mechanism, we propose Temporal-Spatial-LSTM (TS-LSTM), which is able to incorporate both temporal dependencies and spatial correlation. Figure 4.3 illustrate the network structure of TS-LSTM.

The TS-LSTM firstly uses the attentional hidden states $\hat{h}_i^t$ computed by CNN-LSTM-Attn at each node as input for the spatial attention module, which shares the same idea as the relational module. Given a node $j$ we want to predict, the spatial attention module computes relation across pairs between all nodes and the node $j$ by a content-based function $g_\phi$, which is a CNN. The alignment vector $\alpha_{ij}$ is the softmax of $g_\phi$ outputs. The spatially attentional hidden states $\tilde{h}_j^t$ is defined as weighted linear combination of $\hat{h}_i^t$ and its corresponding alignment vector $\alpha_{ij}$, which is then fed into the FC decoder and makes the prediction.

$$
\alpha_{ij} = \text{softmax}(h_i^t, h_j^t) = \frac{\exp(g_\phi(h_i^t, h_j^t))}{\sum_{i'} \exp(g_\phi(h_{i'}^t, h_j^t))} 
$$

$$
\tilde{h}_j^t = \sum_i \alpha_{ij} \hat{h}_i^t \tag{4.6}
$$

During training stage, for a faster convergence, the CNN-LSTM-Attn is pre-trained
while other parameters are initialized randomly. We can simply understand the design of TS-LSTM that CNN-LSTM-Attn is trained to extract temporal dependencies of each node and the spatial attention module learns to infer spatial dependencies across pairs of nodes. The spatial attention module is not necessarily privy to which relations between nodes actually exist, nor the actual meaning of any particular relation. Thus, the spatial attention module must learn to unearth the implication and existence of spatial relations without specification and supervision. Moreover, as the spatial relational module is rather flexible, nodes with trivial spatial correlation implied by prior knowledge can be dropped.

**Figure 4.3:** TS-LSTM network structure.

4.5 **Implementation**

The implementation of deep neural networks is based on TensorLayer (Dong et al. (2017a)), which is a high-level library of TensorFlow (Abadi et al. (2015)). Our design pattern takes advantage of functional programming and object-oriented programming and provides agile project development with simple structure, friendly interfaces, minimum redundancy and sufficient flexibility.

Figure 4.4 demonstrates the structure of our project.

1. The green section supports data refinery, data analysis and data loading for
controllers. Results of data analysis and methods of data refinery have been discussed in Chapter 3.

2. In the blue section, we firstly defines a base model, which integrates several fundamental interfaces including placeholders, training operations, loss functions, network structure and models (Source Code 4.1). New deep neural networks inherit the base model and acquire all features of the superclass. The only modification needed is to update the network structure. Besides, methods can be overrode if any other interfaces need updating. For example, we can firstly build a simple RNN for the prediction problem, and then other models can share the same definitions of input, output, loss functions and optimisers, but only a new network structure.

3. The orange section implements controllers and applications. Similarly, the base controller defines the training, testing and inference process (Source code 4.2). Some functionalities such as model saving/loading can be also implemented within the base controller. Generally, there should be one controller corresponds with each DNN model. Most controllers share exactly same process for training/testing/inference, so we only need to update some basic settings e.g. path of directory for logging.

Figure 4.4: Project structure. All deep neural network models are implemented based on TensorLayer and the base model. Given the model and refined data, the controller defines the process for training, validation, testing and inference. Applications including analysis and visualisation is built upon prediction results.
4.5. IMPLEMENTATION

Source Code 4.1: An example of implementation of the base model, which will be inherited and overridden by other DNN models. As most models share same definition of input, output, loss functions and optimisers, only minor changes needed in child classes.

```python
import tensorflow as tf
import tensorlayer as tl

# Base model
class Model():
    # Initialisation of the model
    def __init__(self, model_name):
        # model name will be used as scope of variables
        self.model_name = model_name

        # Definition of placeholders for input, output
        # And other placeholders if necessary
        def __create_placeholders__(self):
            # x = tf.placeholders
            # y = tf.placeholders
            pass

        # Deep neural network structure
        # Needs to be updated for different models
        def __get_network__(self, x, is_train, reuse):
            pass

        # Definition of train_net for training
        # Definition of test_net for validation, testing and inference
        def __create_model__(self):
            # train_net = self.__get_network__(x, is_train=True, reuse=False)
            # test_net = self.__get_network__(x, is_train=False, reuse=True)
            pass

        # Definition of loss functions
        def __create_loss__(self):
            pass

        # Definition of optimisers, learning rate decay policy
        # And other training operations if necessary
        def __create_training_op__(self):
            pass
```


Source Code 4.2: An example of implementation of the base controller, which will be inherited and overrode by other controllers. As some models may share exactly the same training, testing and inference process, we only need to modify some basic settings e.g. path of directory for logging.

```python
import tensorflow as tf
import tensorlayer as tl

# Base controller
class Controller:

    # Initialisation of controller
    def __init__(self, model):
        # the deep neural network model
        self.model = model

    # Definition of inference
    def __test_sequence__(self, epoch, test_batch_x, test_batch_y):
        pass

    # Definition of validation and testing
    def __valid_test__(self, epoch, test_batch_x, test_batch_y):
        pass

    # Definition of training
    def __train__(self, epoch, train_batch_x, train_batch_y):
        pass

    # Controller for inference
    def controller_test_sequence(self):
        # load testing data node by node
        # then call self.__test_sequence__()
        # get prediction results and save
        pass

    # Controller for testing
    def controller_test(self):
        # load testing set then call self.__valid_test__()
        pass

    # Controller for training
    def controller_train(self):
        # load training set then call self.__train__()
        # meanwhile, load validation set and call self.__valid_test__()
        pass
```
Chapter 5

Experiments and Evaluation

We finished two tasks to demonstrate the outstanding performance of our proposed methodologies. Task one is to predict traffic volume on the Highways England dataset and compare our models with baselines quantitatively. The second task is exactly same as KDDCUP 2017 traffic volume prediction and we will demonstrate that our model outperforms the model that got 1st place in the competition. In this chapter, we will firstly introduce some basic information and settings of experiments and models. Then we will quantitatively compare our models with baselines in the two tasks, and analyse the experimental results. Thirdly, based on the forecasting results, we will demonstrate some interesting discoveries and potential applications. Finally, the visualisation system and demonstration will be covered at the end of this chapter.

5.1 Basic Information

5.1.1 Tasks

Task 1: Traffic volume prediction on the Highways England dataset. Given traffic data of the past day (96 observations) or week (672 observations), the goal is to predict number of vehicles in the next 2 hours with 15-minute time intervals (8 observations). This task tries to demonstrate outstanding stability and accuracy of our proposed methodologies.

Task 2: Traffic volume prediction on the KDDCUP 2017 dataset. Similarly, given traffic data of the past week, 2-hour traffic data prior testing period and environment factors, the goal is to predict number of vehicle in the 2 hours specified as illustrated by Figure 3.2. This task tries to show that our model outperforms than the model
which got first place in the competition.

### 5.1.2 Datasets Partition

An essential and fundamental rule of traffic prediction problem is that we should not use observations in the future to predict those in the past. Therefore, when splitting training set and testing set, we strictly follow the rule and guarantee that the testing set is after the training set.

The Highways England dataset is divided into three parts. We use data from 01/01/2016 to 30/09/2016 as training set, 01/10/2016 to 31/12/2016 as validation set and data from 01/01/2017 to 30/06/2017 as testing set.

For the KDDCUP 2017 dataset, as described in Section 3.1.2 and Figure 3.2, we use data of traffic volume from 19/09/2016 to 10/10/2016 as training set, the week 11/10/2016 to 17/10/2016 as validation set, and 18/10/2016 to 24/10/2016 as testing set. In the testing set, we only need to predict traffic volume during 8-10am and 17-19pm each day, and data 2-hour prior the testing slices is given as a reference.

During training period, validation set is firstly used as a indicator for early stopping to prevent overfitting, and then fed back into training (Goodfellow et al. (2016)) before the model is applied on the testing set.

<table>
<thead>
<tr>
<th>Datasets partition in experiments.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Highways England dataset</strong></td>
</tr>
<tr>
<td><strong>Train</strong></td>
</tr>
<tr>
<td>Start: 01/01/2016</td>
</tr>
<tr>
<td>End: 30/09/2016</td>
</tr>
<tr>
<td>Full Batch Size: 1,136,290</td>
</tr>
<tr>
<td><strong>Valid</strong></td>
</tr>
<tr>
<td>Start: 01/10/2016</td>
</tr>
<tr>
<td>End: 31/12/2016</td>
</tr>
<tr>
<td>Full Batch Size: 387,860</td>
</tr>
<tr>
<td><strong>Test</strong></td>
</tr>
<tr>
<td>Start: 01/01/2017</td>
</tr>
<tr>
<td>End: 30/06/2017</td>
</tr>
<tr>
<td>Full Batch Size: 814,292</td>
</tr>
</tbody>
</table>

| **KDDCUP 17 dataset**             |
| **Train**                         |
| Start: 19/09/2016                 |
| End: 10/10/2016                   |
| Full Batch Size: 3456              |
| **Valid**                         |
| Start: 11/10/2016                 |
| End: 17/10/2016                   |
| **Test**                          |
| Start: 18/10/2016                 |
| End: 24/10/2016                   |
| Full Batch Size: 14               |

### 5.1.3 Evaluation Metrics

MAPE (Mean Absolute Percentage Error) is applied as the final evaluation metrics and also used as the loss function to update parameters of deep neural networks.
Mathematically, MAPE is defined as:

\[
MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|y_i - t_i|}{t_i}
\]  

(5.1)

where \(t_i\) is ground truth and \(y_i\) is prediction.

In the early stage of training, we use MSE (Mean Square Error) to speed up parameters optimisation, as MSE is more sensitive to error with large absolute value, which can help to fit data with large values like traffic during peak hours more quickly.

\[
MSE = \sum_{i=1}^{N} (y_i - t_i)^2
\]

(5.2)

5.2 Models Settings

5.2.1 Baselines

**SARIMA** uses order (1, 0, 1) for ARIMA and seasonal order (1, 1, 0, 96). **VAR** uses order 1 for autoregressive process. 44 nodes, rather than all 52, are used for prediction due to missing and invalid observations in some nodes. Both SARIMA and VAR are implemented by the StatsModels. **Gaussian Process (GP)** uses Matérn covariance function as the kernel with length scale \(l = 8\) and \(\nu = 0.5\). **Support Vector Regression (SVR)** uses linear kernel with default penalty parameter \(C = 1\) of the error term. Both GP and SVR are implemented by the scikit-learn. All the four baseline models are tested on the Highways England dataset only.

5.2.2 DNN

Table 5.2 summarises the structure of the CNN-LSTM-Attn and details of some training settings for Task 1. The structure of TS-LSTM is included in Table 5.3. Only one CNN-LSTM-Attn and one TS-LSTM will be trained for the whole transportation network.

Only CNN-LSTM-Attn has been tested on the KDDCUP 17 dataset because prior knowledge for spatial correlation is unclear. The settings of CNN-LSTM-Attn for KDDCUP17 dataset is mostly same as Table 5.2. In the testing set of KDDCUP17,

---

we only need to predict traffic volume at 8-10am and 5-7pm given ground truth at 6-8am and 3-5pm as shown in Figure 3.2. Therefore, during training and inference, we use historical data in highly related time period as input, illustrated in Figure 5.1, rather that all observations in the previous week.

By default, all the baseline and DNN models use previous one-week observations as input for training and inference.

**Table 5.2:** Settings of CNN-LSTM-Attn for Highways England dataset.

<table>
<thead>
<tr>
<th>Layers</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input</strong></td>
<td>One-week observations by default. The size (7, 96, 2) refers to 7 days a week, 96 data points a day and 2 features per each data point (traffic volume + type of day). We use mini-batch with batch size 128.</td>
</tr>
<tr>
<td><strong>CNN</strong></td>
<td>Two-layer 2D CNN with ReLU and max pooling. The first convolutional layer has 16 filters and each filter is (7 \times 8) with strides (1 \times 1). The first max pooling layer has a filter size (1 \times 2) with strides (1 \times 2). The second convolutional layer has 32 filters and each filter is (7 \times 4) with strides (1 \times 1). The second max pooling layer has a filter size (7 \times 2) with strides (7 \times 2).</td>
</tr>
<tr>
<td><strong>RNN</strong></td>
<td>Single-layer LSTM as cell with 256 units of the hidden state.</td>
</tr>
<tr>
<td><strong>FC</strong></td>
<td>Two fully connected layers with two dropout layers. The first FC layer has 128 units and the second has 8 units. Both FC layers use identity activation function. Both dropout layers keep 80% parameters when training.</td>
</tr>
<tr>
<td><strong>Notes</strong></td>
<td>Parameters are all initialized randomly by uniform distribution between ([-0.05, 0.05]). Adam optimiser is applied for parameter optimisation (Kingma and Ba (2014)). MSE is used as loss function in early training stage, then MAPE. The learning rate is initially set as 0.002 and exponentially decays with rate 0.8 every two epochs.</td>
</tr>
</tbody>
</table>

**Table 5.3:** Settings of TS-LSTM for the Highways England dataset.

<table>
<thead>
<tr>
<th>Layers</th>
<th>Settings</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CNN-LSTM-Attn</strong></td>
<td>Same as the settings in Table 5.2. 44 nodes are used and mini-batch with batch size 32.</td>
</tr>
<tr>
<td>(g_{\phi})</td>
<td>Three-layer 2D CNN with ReLU and max pooling, and three fully connected layers with two dropout layers. The output has only one unit which is (\alpha_{ij}).</td>
</tr>
<tr>
<td><strong>Notes</strong></td>
<td>Parameters are all initialized randomly by uniform distribution between ([-0.05, 0.05]). Adam optimiser is applied for updating. CNN-LSTM-Attn is pre-trained.</td>
</tr>
</tbody>
</table>

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5.3. EXPERIMENTAL RESULTS

Task 1: On the Highways England dataset, we quantitatively compare performance of the baselines with DNNs. Table 5.4 has shown that CNN-LSTM-Attn achieves best performance with overall 9.26% error rate on the testing set, lowest compared with all other models. Besides, in longer term prediction, CNN-LSTM-Attn is more stable and accurate.

However, TS-LSTM is less accurate than CNN-LSTM-Attn and only demonstrates comparable performance with LSTM. Many reasons as cited below may lead to underfitting, which can be solved if more time is allowed for this project in the future.

1. Local region: The nodes selected in the Highways England dataset are distributed in a relative small region with high average speed, which means the average journey time in the region is short (12 minutes estimated by Google Map on M4 from Brentford to Slough, London), even shorter than the sampling interval (15 minutes). Section 3.3 demonstrates strong correlation among specific nodes but the influence happened with minor delay almost simultaneously. Therefore, prediction improvement, especially for longer term, with information from other nodes can be very limited.

2. Complexity: As prior knowledge is not necessarily needed for the spatial attention mechanism, the module must learn to extract relations across every pair of nodes. Given $N$ nodes, there are $N^2$ pairs that the module needs to learn. Therefore, with more nodes, the complexity of TS-LSTM grows explo-
sively and more parameters are necessary to prevent underfitting. Moreover, the
depth of TS-LSTM is doubled than CNN-LSTM-Attn, so the efficiency of
updating parameters is also a concern.

Table 5.5 quantitatively compares performance among different DNNs. Both global
attention mechanism and CNN embedding can effectively encode temporal depen-
dencies in traffic prediction and have achieved improvement with lower MAPE than
the raw LSTM. Besides, CNN is more efficient than the attention mechanism espe-
cially for longer term prediction.

Table 5.6 demonstrates longer observations can lead to higher accuracy. One-day
observations are used as input of CNN-LSTM-Attn and compared with the CNN-
LSTM-Attn fed by one-week observations. Experiments have shown that the latter
one achieves lower MAPE. Intuitively, with only one-day observations, the model is
more vulnerable and prone to variance of traffic data on that day, but CNN-LSTM-
Attn with one-week observations is more robust as more historical data is taken into
consideration.

Table 5.4: MAPE (%) on the Highways England testing set. CNN-LSTM-Attn achieves
best overall performance with lowest error rate 9.26%.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>SARIMA</th>
<th>VAR</th>
<th>GP</th>
<th>SVR</th>
<th>LSTM</th>
<th>CNN-LSTM-Attn</th>
<th>TS-LSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>15-min</td>
<td>8.99</td>
<td>12.15</td>
<td>9.48</td>
<td>7.73</td>
<td>7.54</td>
<td>8.53</td>
<td></td>
</tr>
<tr>
<td>30-min</td>
<td>12.06</td>
<td>19.16</td>
<td>13.23</td>
<td>8.77</td>
<td>8.35</td>
<td>8.50</td>
<td></td>
</tr>
<tr>
<td>45-min</td>
<td>15.09</td>
<td>25.47</td>
<td>17.01</td>
<td>9.51</td>
<td>8.88</td>
<td>9.17</td>
<td></td>
</tr>
<tr>
<td>60-min</td>
<td>18.37</td>
<td>31.17</td>
<td>20.94</td>
<td>10.02</td>
<td>9.25</td>
<td>9.86</td>
<td></td>
</tr>
<tr>
<td>75-min</td>
<td>21.93</td>
<td>36.27</td>
<td>25.14</td>
<td>10.42</td>
<td>9.60</td>
<td>10.33</td>
<td></td>
</tr>
<tr>
<td>90-min</td>
<td>25.74</td>
<td>40.87</td>
<td>29.47</td>
<td>10.74</td>
<td>9.89</td>
<td>10.59</td>
<td></td>
</tr>
<tr>
<td>105-min</td>
<td>29.77</td>
<td>45.03</td>
<td>33.97</td>
<td>11.04</td>
<td>10.12</td>
<td>11.05</td>
<td></td>
</tr>
<tr>
<td>120-min</td>
<td>33.93</td>
<td>48.82</td>
<td>38.64</td>
<td>11.54</td>
<td>10.44</td>
<td>12.07</td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>22.00</td>
<td>20.73</td>
<td>32.37</td>
<td>23.48</td>
<td>9.97</td>
<td>9.26</td>
<td>10.01</td>
</tr>
</tbody>
</table>
Table 5.5: Comparison among different DNNs on the Highways England testing set.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>LSTM</th>
<th>LSTM-Attn</th>
<th>CNN-LSTM</th>
<th>CNN-LSTM-Attn</th>
<th>TS-LSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>15-min</td>
<td>7.73</td>
<td>7.66</td>
<td>7.52</td>
<td>7.54</td>
<td>8.53</td>
</tr>
<tr>
<td>30-min</td>
<td>8.77</td>
<td>8.66</td>
<td>8.35</td>
<td>8.35</td>
<td>8.50</td>
</tr>
<tr>
<td>45-min</td>
<td>9.51</td>
<td>9.35</td>
<td>8.96</td>
<td>8.88</td>
<td>9.17</td>
</tr>
<tr>
<td>60-min</td>
<td>10.02</td>
<td>9.84</td>
<td>9.36</td>
<td>9.25</td>
<td>9.86</td>
</tr>
<tr>
<td>75-min</td>
<td>10.42</td>
<td>10.21</td>
<td>9.70</td>
<td>9.60</td>
<td>10.33</td>
</tr>
<tr>
<td>90-min</td>
<td>10.74</td>
<td>10.48</td>
<td>9.98</td>
<td>9.89</td>
<td>10.59</td>
</tr>
<tr>
<td>105-min</td>
<td>11.04</td>
<td>10.78</td>
<td>10.20</td>
<td>10.12</td>
<td>11.05</td>
</tr>
<tr>
<td>120-min</td>
<td>11.54</td>
<td>11.33</td>
<td>10.55</td>
<td>10.44</td>
<td>12.07</td>
</tr>
<tr>
<td>Overall</td>
<td>9.97</td>
<td>9.79</td>
<td>9.33</td>
<td>9.26</td>
<td>10.01</td>
</tr>
</tbody>
</table>

Table 5.6: Comparison between different length of input on the Highways England testing set.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>CNN-LSTM-Attn&lt;sup&gt;1&lt;/sup&gt;</th>
<th>CNN-LSTM-Attn&lt;sup&gt;2&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>15-min</td>
<td>7.58</td>
<td>7.54</td>
</tr>
<tr>
<td>30-min</td>
<td>8.40</td>
<td>8.35</td>
</tr>
<tr>
<td>45-min</td>
<td>8.98</td>
<td>8.88</td>
</tr>
<tr>
<td>60-min</td>
<td>9.39</td>
<td>9.25</td>
</tr>
<tr>
<td>75-min</td>
<td>9.71</td>
<td>9.60</td>
</tr>
<tr>
<td>90-min</td>
<td>9.97</td>
<td>9.89</td>
</tr>
<tr>
<td>105-min</td>
<td>10.23</td>
<td>10.12</td>
</tr>
<tr>
<td>120-min</td>
<td>10.54</td>
<td>10.44</td>
</tr>
<tr>
<td>Overall</td>
<td>9.35</td>
<td>9.26</td>
</tr>
</tbody>
</table>

<sup>1</sup> Previous one-day observations as input (96 data points).
<sup>2</sup> Previous one-week observations as input (672 data points).

Figure 5.2 shows the learning curves of DNNs. Though CNN-LSTM-Attn with one-week observations has higher MAPE on training set in the very early stage, the error rate drops dramatically later. Because TS-LSTM uses pre-trained CNN-LSTM-Attn as part of its encoder, the learning curves of TS-LSTM drops quicker.
Chapter 5. Experiments and Evaluation  5.3. EXPERIMENTAL RESULTS

**Figure 5.2:** Learning curves of training on the Highways England dataset.

![Learning Curves during Training](image)

Figure 5.3 shows MAPE of CNN-LSTM-Attn at each node. The red line indicates the average overall MAPE 9.26%. As illustrated, CNN-LSTM-Attn achieves overall good prediction accuracy at most nodes. However, the prediction accuracy on 'A' roads including Node 6156-1, 6157-1, 6178-1, 6179-1, 7044-1 and 7045-1 is not as good as that on motorways. Because the average traffic volume on 'A' roads less than one third of that on motorways (Table 3.4), prediction on 'A' roads is more challenging.

**Figure 5.3:** MAPE at each node (CNN-LSTM-Attn) on the Highways England dataset.

![MAPE at each node](image)

**Task 2:** On the KDDCUP 17 dataset, we compare the CNN-LSTM-Attn with one-week observations, which achieves lowest MAPE in the Task 1, and the model that got first place in the competition, which is built upon FC network and decision tree. Table 5.7 shows that CNN-LSTM-Attn achieves lower overall MAPE 10.48 and performs better on the testing set than the model that got first place.
### Table 5.7: MAPE (%) on the KDDCUP 2017 testing set.

<table>
<thead>
<tr>
<th></th>
<th>CNN-LSTM-Attn</th>
<th>The-Model-Got-1st-Place</th>
</tr>
</thead>
<tbody>
<tr>
<td>MAPE</td>
<td><strong>10.48</strong></td>
<td>12.03</td>
</tr>
</tbody>
</table>
Figure 5.4: Prediction at Node 4121 by CNN-LSTM-Attn (15-minute to 1-hour ahead).
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Figure 5.5: Prediction at Node 4121 by CNN-LSTM-Attn (75-minute to 2-hour ahead).
5.4 Analysis and Discovery

5.4.1 Peak Volume Alert

With help from our prediction model CNN-LSTM-Attn, the regulators of motorways can forecast the start of peak hours more precisely and how long it may last 2 hours in advance. The model achieves outstanding accuracy not only on workdays and also weekends and the bank holiday (1st May 2017). Figure 5.6 highlights the borderline of peak hours by the red lines and demonstrates our model can potentially be applied for early alert of peak traffic volume.

Figure 5.6: High volume alert based on 2-hour prediction by CNN-LSTM-Attn.
5.4.2 Abnormal Detection

The traffic can be blocked or delayed by unexpected accidents or events, and such abnormal conditions are also reflected by abnormal traffic volume during specific hours. Figure 5.7, 5.8 and 5.9 demonstrate significant outliers which lead to high error rate of our prediction model and slightly affect forecasting in the following hours. Each outlier corresponds with a piece of news, which includes causes of unusual conditions on M4 and M25 and is screen captured from Twitter.

Figure 5.7: Abnormal traffic condition on M25 on 16th Jun 2017.

Figure 5.8: Abnormal traffic condition on M25 on 21st May 2017.

Figure 5.9: Abnormal traffic condition on M4 on 16th Feb 2017.

3Twitter @WazeTrafficLON: https://twitter.com/wazetrafficlon, accessed: 2017-09-04.
5.5 Visualisation

GDO provides a straightforward, efficient and attractive visualisation experience to demonstrate results of discovery and evaluation of the forecasting model. In this project, we visualise analytic and experimental results of the Highways England dataset.

The visualisation system is built upon the Section Mode of GDO framework. In Section Mode, the screen wall is split into five sections and each section is an individual web browser. Besides, there is a separated control panel, which is also a web browser.

The communication between six browsers is supported by Node.js and Socket.IO as shown in Figure 5.10. The commands will be sent out from the control panel and firstly received by the server. Then the server will distribute the command to related sections and the browsers that receive the command will react accordingly. The control panel is the only way for users to interactive with the GDO, so there is no need to reverse the message transmission from the sections back to the control panel.

Figure 5.10: Visualisation system structure. There are six browser-based screen, including five sections on the GDO and one control panel. The Node.js server distributes messages/commands coming from the control panel to the GDO and the five sections will react accordingly. The communication channel is built by Socket.IO.

The visualisation on each screen is summarised as below. You can find the panoramic view of visualisation on GDO in Figure 5.17.

1. Section B: Temporal analysis. As shown in Figure 5.11, the first row shows the decreasing of traffic volume on special days, including weekends, Christmas Day and New Year’s Day, and the nine figures below compare different patterns, including start and end of peak hours, between workdays and special days.

2. Section C: Spatial correlation. Based on the coefficient correlation matrix com-
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computed by the VAR, an animated heatmap built by Google Map API \(^4\) highlights spatial correlation between a given node (labelled by a flag) and others (Figure 5.12). The region with reddish colour and relatively large radius indicates stronger correlation between those nodes and the given node. The animation is controlled by the control panel and the given node varies in each frame.

3. Section D: Animated heatmap of traffic volume (ground truth) at each node in the transportation network (Figure 5.13). The reddish region indicates heavy traffic volume and the greenish nodes have fewer vehicles. The animation is controlled by the control panel.

4. Section E: Animated heatmap of traffic volume (2-hour prediction) at each node in the transportation network (Figure 5.14). Similarly, the reddish region indicates large number of vehicles and the greenish nodes are relatively quieter. The animation is also controlled by the control panel and the simultaneousness between Section D and E can help us evaluate accuracy of our forecasting model intuitively.

5. Section A: Prediction accuracy ((Figure 5.15)). The line charts compares ground truth and our prediction. The numbers on the right are the MAPE of our forecasting model (CNN-LSTM-Attn).

6. Control panel: It only has a start button and stop button to control the animations in Section C, D, E ((Figure 5.16)).

Figure 5.11: Visualisation on Section B of GDO: temporal analysis. Comparison of traffic volume and patterns between workdays and special days.

---

Figure 5.12: Visualisation on Section C of GDO: spatial correlation. An animated heatmap based on coefficient matrix computed by the VAR.

Figure 5.13: Visualisation on Section D of GDO: animated heatmap of traffic volume in the network (ground truth).
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Figure 5.14: Visualisation on Section E of GDO: animated heatmap of traffic volume in the network (2-hour prediction).

Figure 5.15: Visualisation on Section A of GDO: prediction accuracy of the CNN-LSTM-Attn model.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>30 Mins</td>
<td>8.35%</td>
</tr>
<tr>
<td>60 Mins</td>
<td>9.25%</td>
</tr>
<tr>
<td>90 Mins</td>
<td>9.89%</td>
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Figure 5.16: Control panel. Controlling the start/stop of animations in Section C, D, E.

Figure 5.17: The panoramic view of visualisation on GDO.
Chapter 6

Conclusions and Future Work

6.1 Conclusions

In this project, we propose two deep learning models, CNN-LSTM-Attn and TS-LSTM, to model temporal and spatial features of traffic volume for short-term prediction (2-hour ahead). Our research includes two traffic datasets, the Highways England dataset and the KDDCUP17 dataset. We firstly analyse temporal pattern and spatial correlation on the Highways England dataset and statistics lead to conclusions:

1. Traffic volume on motorways triple that on 'A' roads. The peak hours on workdays start 7-8am and end 19-20pm on average. Abnormal traffic volume can be detected but corresponding reasons are unavailable in our datasets.

2. Traffic volume has strong and continuous daily seasonality, and clear first-order autoregressive pattern, both of which are fundamental and essential for short-term traffic volume prediction.

3. Special days including weekends, bank holidays, Christmas holidays and New Year's Day have significantly different traffic patterns than workdays. The differences include lower traffic volume, later start of peak hours and various end of peak hours.

4. Evidences indicate that traffic on the same direction of the same motorways is highly correlated and has stronger influence on following nodes around crossroads. However, information from opposite direction is very limited. Severe block or delay can influence traffic in corresponding local region, especially following nodes on the same direction.

In this project, SARIMA, VAR, Gaussian Process and Support Vector Regression are used as baselines, and the limitations of the baselines are also obvious.
1. SARIMA integrates repeating daily traffic pattern effectively but is not sensitive to special or recent conditions. Besides, multiple SARIMAs are needed for multiple locations, because one SAIRMA cannot fit difference sequences.

2. VAR is able to incorporate correlation among nodes, but can easily affected by noises in previous observations.

3. Gaussian Process can approximate interpolation of given observations but the variance of prediction in further future may go outrage.

4. Support Vector Regression with RBF kernel may result in overfitting if the sequence is not smooth enough and linear kernel fails to achieve good accuracy for longer-ahead forecasting.

We proposed CNN-LSTM-Attn to model temporal dependencies, and TS-LSTM which is built upon CNN-LSTM-Attn with spatial relation module to extract spatial correlation. Both CNN-LSTM-Attn and TS-LSTM outperform the baselines on the 2-hour traffic volume prediction on the Highways England dataset with overall MAPE 9.26% and 10.01% respectively. Not only on workdays, prediction on weekends and bank holidays are also highly accurate. Both the CNN embedding and global attention mechanism can effectively encode temporal dependencies and improve prediction accuracy. In addition, using previous one-week rather one-day observations as input also leads to higher accuracy. Besides, the CNN-LSTM-Attn achieves overall outstanding prediction accuracy at most nodes but performance on 'A' roads is not as good as that on motorways. Moreover, TS-LSTM fails to achieve comparable performance with CNN-LSTM-Attn due to lack of significant long term spatial correlation and complexity of the model, which we believe can be solved if more time is allowed for this project.

On the KDDCUP17 dataset, the CNN-LSTM-Attn achieves better accuracy with lower MAPE 10.48% than that 12.03% of the model which got first place in the competition.

With accurate 2-hour traffic forecasting, which is longer than previous literature (30-minute), we believe that our models can potentially applied for peak volume alert and abnormal traffic detection. Unusual traffic news from Twitter have shown that severe delay can be reflected by large error rate of the prediction.

The DNN models are implemented based on TensorLayer, and our design pattern takes advantages of functional programming and object-oriented programming, which provides agile project development with simple structure, friendly interfaces, minimum redundancy and sufficient flexibility. Furthermore, visualisation and animation on the GDO Section Mode help us demonstrate results of discovery and evaluation of the forecasting model.
6.2 Future Work

If more time is allowed for this project, there are some potentially interesting works that can be explored.

1. Improvement of the CNN-LSTM-Attn especially at the nodes that prediction is not accurate enough.

2. Simplifying the TS-LSTM with prior knowledge on the transportation network. Scenario in a larger region and investigation on spatial correlation during holidays among popular locations for tourism would be needed and attractive. Further research on how abnormal volume (extremely high or low) may affect neighbouring locations quantitatively can be useful for motorways regulators.

3. Visualisation of the features extracted by CNN, RNN and the attention mechanism can help us understand how deep neural networks work on time series analysis.

4. The Highways England dataset includes 52 monitoring nodes around Heathrow Airport and Uxbridge. More nodes in a larger region can be used to train a more general and powerful DNN model.

5. So far, only traffic data on motorways and 'A' roads in suburban area has been used. If tick-level traffic data in urban area is available, the same idea can be applied to use DNNs modelling temporal and spatial features. As traffic can be affected by traffic lights in urban area, further research on optimisation of length of the traffic lights based on forecasting by deep learning can be helpful to prevent severe traffic congestion.

6. Accident data is not available in current datasets but can be collected for analysis on how unexpected accidents may affect local traffic and how to make detection of such abnormal conditions more efficiently with leverage from deep learning.

7. Future research on relation between traffic volume and air pollution especially how traffic volume prediction may help to improve air quality monitoring and forecasting can be useful for both residents and governors.
Bibliography


Chapter 7

Appendices

7.1 Dataset

Table 7.1: Detailed information and locations of the 52 nodes selected in the Highways England dataset. Distribution of the nodes on map can be found in Figure 3.1.

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### Chapter 7. Appendices

#### 7.1. Dataset

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