Motorway Flow Prediction using Advanced Deep Learning Methods - Final student Report

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1. Summarized Objective

The motorways along the Sydney region are equipped with traffic count detectors, which record the number of vehicle passing by in a dedicated time slot. The data collected from these sensors will be referenced in the paper as 'motorway traffic flow'. One important problem is that based on the collected data of motorway traffic flow, how to predict congestion along motorways using extensive data-driven technologies? As long as we can predict when and where the future congestion will appear, people can take early action to prevent it.

The challenges of traffic flow prediction includes the various data outliers, the temporal-spatial correlation of data and the stochastic of traffic flow itself and also external events, such as incidents. Moreover, there are only small numbers of predictor which is designed for time-dependent and spatial correlation prediction task. Our work focuses on finding the best methods for the motorway traffic flow prediction.

In this work, we firstly conduct a data profiling on the given data set. We find the data set includes various outliers and the traffic flow data is not always continuous in time. Then we propose some methods for cleaning and processing of the data. Finally, we apply some well-known neural network models for the prediction problem and compare their performance in different situations.

2. Data Profiling

2.1. Data characteristics

Our data set covers a whole year (2017) of traffic flow data which includes two sections of expressway in Sydney, called M2 and M7 respectively. M2 expressway consists of 66 sensors and M7 expressway has 208 sensors. The travel flow data for each station is recorded every 3 minutes (e.g. 00:00, 00:03, ... , 23:57). Figure 1 illustrates several locations of stations on each road segment of M2, while Figure 2 is for M7. From the two figures, we know that these stations are consecutive in space and connected closely. Therefore, there must exist some spatial and temporal correlations between the stations of a highway.

More specifically, there are mainly three kinds of relations among these stations which are represented in Figure 3, where each circle represents a station.

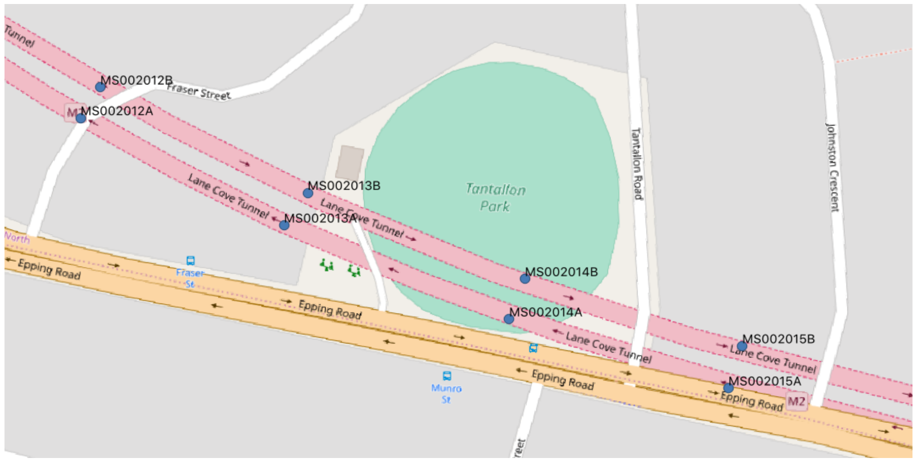


Figure 1: Road segments investigated for traffic flow prediction(M2)

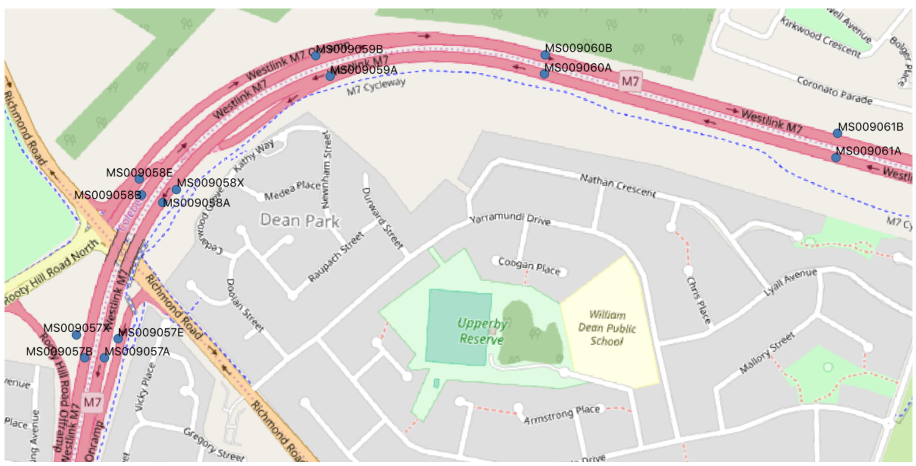


Figure 2: Road segments investigated for traffic flow prediction(M7)

We take several stations for corresponding cases as an example and analyze the traffic flow relation. The stations named after A are Motorway Flow Prediction using Advanced Deep Learning Methods - Final student Report Haowen Li, Zongyang He Supervisors: Adriana-Simona Mihaita, Marian-Andrei Rizoiu January 2019 1 Summarized Objective The motorways along the Sydney region are equipped with traffic count detec- tors, which record the number of vehicle passing by in a dedicated time slot. The data collected from these sensors will be referenced in the paper as 'motor- way traffic flow'. One important problem is that based on the collected data of motorway traffic flow, how to predict congestion along motorways using exten- sive data-driven technologies? As long as we can predict when and where the future congestion will appear, people can take early action to prevent it. The challenges of traffic flow prediction includes the various data outliers, the temporal-spatial correlation of data and the stochastic of traffic flow itself and also external events, such as incidents. Moreover, there are only small num- bers of predictor which is designed for time-dependent and spatial correlation prediction task. Our work focuses on finding the best methods for the motorway traffic flow prediction. In this work, we firstly conduct a data profiling on the given data set. We find the data set includes various outliers and the traffic flow data is not always continuous in time. Then we propose some methods for cleaning and processing of the data. Finally, we apply some well-known neural network models for the prediction problem and compare their performance in different situations. 2 Data Profiling 2.1 Data characteristics Our data set covers a whole year (2017) of traffic flow data which includes two sections of expressway in Sydney, called M2 and M7 respectively. M2 expressway consists of 66 sensors and M7 expressway has 208 sensors. The travel flow data for each station is recorded every 3 minutes (e.g. 00:00, 00:03, ... , 23:57). Figure 1 illustrates several locations of stations on each road segment of M2, while Figure 2 is for M7. From the two figures, we know that these stations are 1 consecutive in space and connected closely. Therefore, there must exist some spatial and temporal correlations between the stations of a highway. Figure 1: Road segments investigated for traffic flow prediction(M2) Figure 2: Road segments investigated for traffic flow prediction(M7) More specifically, there are mainly three kinds of relations among these sta- tions which are represented in Figure 3, where each circle represents a station. We take several stations for corresponding cases as an example and analyze the traffic flow relation. The stations named after A are considered to be regular detector set-ups on the main road. When the traffic from station '...A' exits towards '...X' and we consider it as an 'exit' set-up. Likewise, when the traffic enters '...A' from '...E' and we consider it as an 'entrance' set-up. Therefore, 2 considered to be regular detector set-ups on the main road. When the traffic from station '...A' exits towards '...X' and we consider it as an 'exit' set-up. Likewise, when the traffic enters '...A' from '...E' and we consider it as an 'entrance' set-up. Therefore, for better distinguish, the exit stations are named after the end of X and the entrance stations are named after the end of E. The case 1 shows that two stations are connected directly on the main road. Thus, the traffic flow of these two stations should be similar at the same time. Sub figure 'a' of figure 4 takes two stations labelled as 'MS009018A' and 'MS009019A' as an example, and it can confirm this relation for case 1. As for case 2, it shows that there is an exit after 4A, thus we know that the traffic flow of 4A should be similar to the sum of the flow number of 3A and 3X. Sub figure 'b' of figure 4 confirms the spatial relation theory mentioned above by presenting all investigation on 3 stations labelled 'MS009003X', 'MS009004A' and 'MS009003A'. From the network structure, we know that 'MS009003X' is an exit after 'MS009004A'. Thus the sum of the traffic flow of 'MS009003A' and 'MS009003X' is similar to the value of 'MS009004A'. Likewise, the case 3 shows that there is an entrance before 11A, thus we know that the traffic flow of 11A should be similar to the sum of the flow number of 12A and 12E. Also, the sub figure 'c' can confirm the relation theory for case 3.

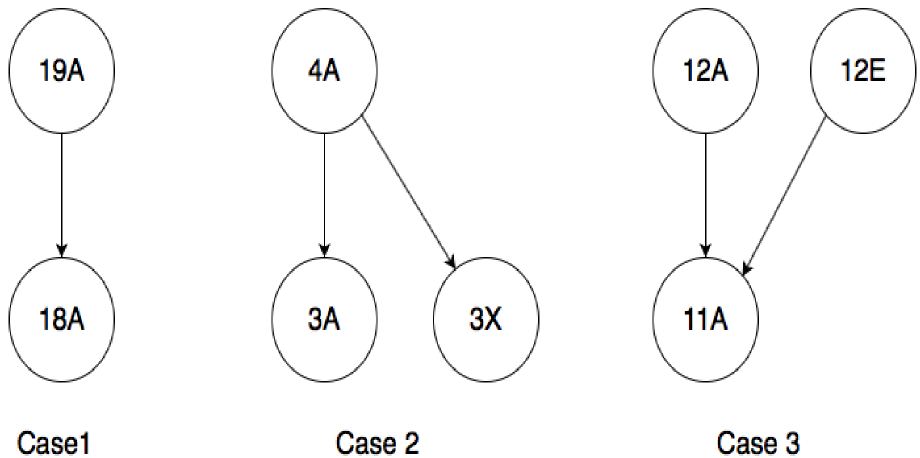
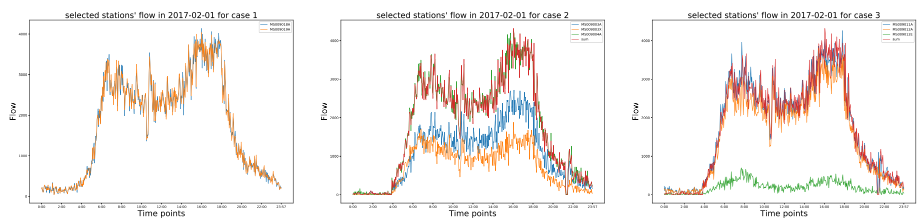


Figure 3: Three possible cases of connected stations along Sydney motorways



(a) Case 1 (b) Case 2 (c) Case 3

Figure 4: The traffic flow value of several stations for corresponding cases in figure 3 in 2017-02-01. Sub figure 'a' is for case 1. Sub figure 'b' is for case 2. Sub figure 'c' is for case 3.

2.2. Data analysis

As a first step in our data analysis, we choose 80 continuous stations in one direction on the main road to explore the traffic flow change during a regular day. Figure 5 shows a time-space diagram of the traffic flows of a section of highway in one direction. The time-space diagram is calculated using the volume-to-capacity ration, and evaluated using the Benchmark in NSW, Australia. For details, we set the capacity as 4000 because it is a large volume and it will cause traffic congestion if the volume exceeds this number. It clearly shows that there are two peak periods per day, which are during 6:30–8:30 and 15:30–18:00, respectively. Also, the 80 continuous stations have a similar traffic flow trend during the day, for both congested and un-congested periods.

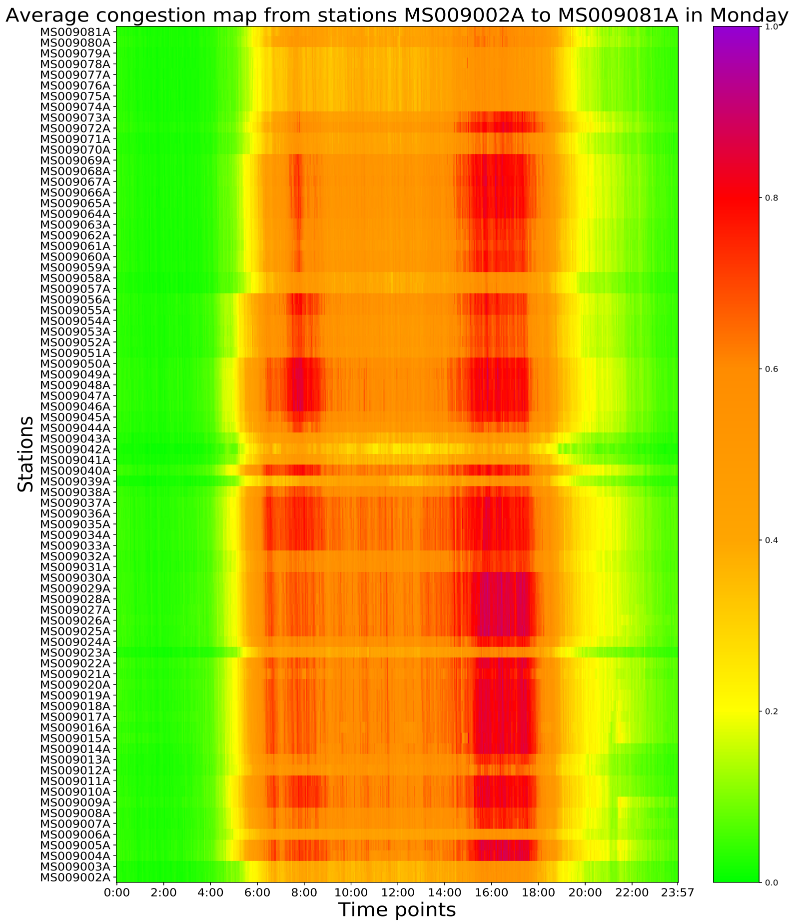


Figure 5: A time-space diagram that shows average traffic flow of stations from 'MS009002A' to 'MS009002A', measured by all Mondays from Feb to Apr in 2017. Red means great traffic flow and green means little traffic flow.

By continuing our analysis, we further detail our findings on the traffic flow along motorways. From figure 6, we observe that the traffic flow trend is similar among weekdays and the flow value is relatively smaller during weekends especially on the two traffic peak periods mentioned above. Therefore, Figure 7 shows cases what an "abnormal" traffic flow would look like compared to historical mean traffic flow. In this figure, orange represents the average flow recorded at the "MS009050A" station on Mondays, while Green and Blue represent the 80 and 20 traffic flow percentile respectively. This translates that on a regular Tuesday, the traffic flow at this station is expected to fall either around the average traffic flow or inside the historical confidence interval. This does not seem to be the case for Tuesday, 25th of April, 2017, which is the ANZAC day (blue plotted line). Building any type of prediction models would take into consideration possible outliers that may appear either due to public holidays or random events like accidents or extreme weather condition. The profiled traffic flow helps us to understand what is considered as "expected" traffic congested, versus abnormal situations (accidents) which do not follow a historical trend.

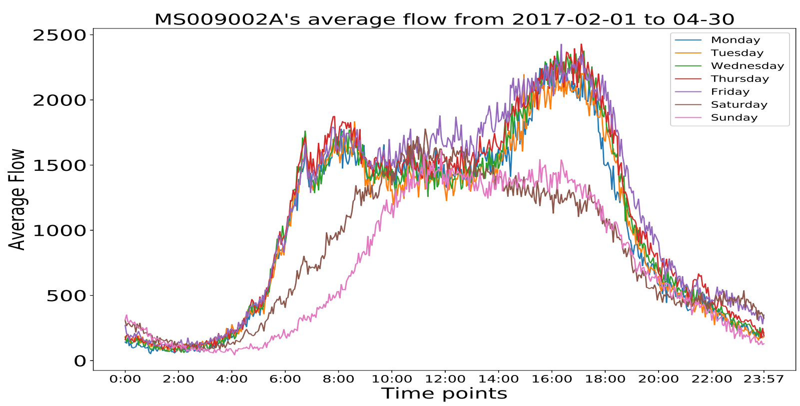


Figure 6: MS009002A's average flow from 2017-02-01 to 04-30 at every specific time point of each weekday and weekend.

3. Data Processing and Outlier Identification

Figure 8 measures the outliers detection during the whole data set, aggregated by month. We observe that December and May have more missing data points than the rest of months. For an efficient and precise prediction, we exclude these two months' data. Because continuous data set is needed as well, we choose the data from February to April for our model training, validation and testing. Specifically, we use the data from February to March to do the model training, and use the data on the first half month in April to do the validation. Finally, we use the other half month in April to do the testing. As for these missing data points, there are several ways to do interpolation. Firstly, we use the same time point value of the previous day or next day to fulfill the missing value. However, from Figure 6, we know that there are significant differences between weekdays and weekends and while this might work efficiently during the week, the difference between Friday and Saturday or Sunday might be big

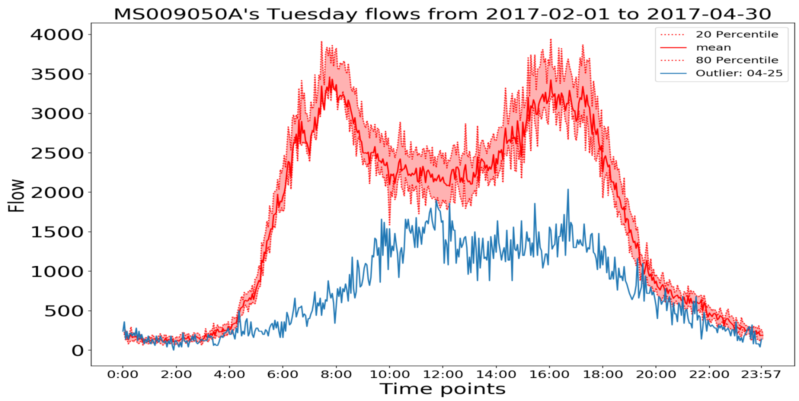


Figure 7: The red solid line represents the average value of flow for MS009050A station from 2017-02-01 to 2017-04-30. We order the flow at every time point of each Monday value. If the flow is in the top 20 percentile, we plot that as a sparse red dotted line while if the flow is in the minimum 20 percentile, we plot that as a red dense dotted line. The blue line means the day which contains most outliers (less than minimum 20 percent value, larger than top 20 percent value) which corresponds to the ANZAC day.

and led to erroneous information of the traffic flow. Secondly, we can compute the average of the previous time point value and the next time point value to fulfill it. However, sometimes there are too many (more than 10) continuous missing data points, thus making it hard to get a good ”representative” average. After comparing different methods, we finally use the average of the same time points from all weeks in a month. For example, if the data set misses a data point at 2:00 pm in April 3rd which is a Monday, then we compute the average of data points at 2:00 pm on all Mondays of April (Apr 10th, 17th, 24th) and use it to fulfill the missing value.

4. Prediction Algorithms

After the data profiling, cleaning and outlier identification, we proceed to test various prediction models which we want to test and compare.

We denote the input of our model as $X = (X^t, X^{t-1}, ..., X^{t-r+1})$, where r is the number of time points we used to train our model for the prediction and t is the current time point. X^t is consisted by all stations' flow at a time point t. $X^t = (X_1^t, X_2^t, ..., X_n^t)$ where n is the number of stations. Our prediction target is $X^{t+p} = (X_1^{t+p}, X_2^{t+p}, ..., X_n^{t+p})$ where p denotes how far in the future we want to make the prediction. A general prediction model can be described by the following figure.

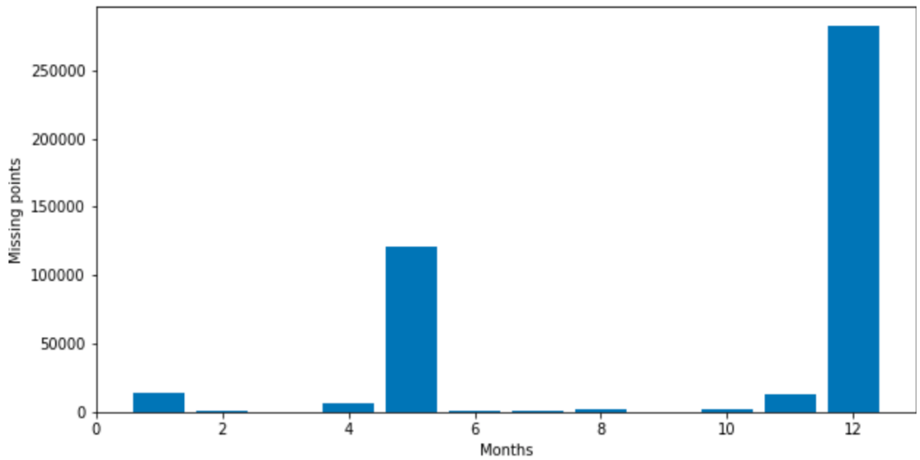


Figure 8: The number of missing points of M7 in each month of 2017

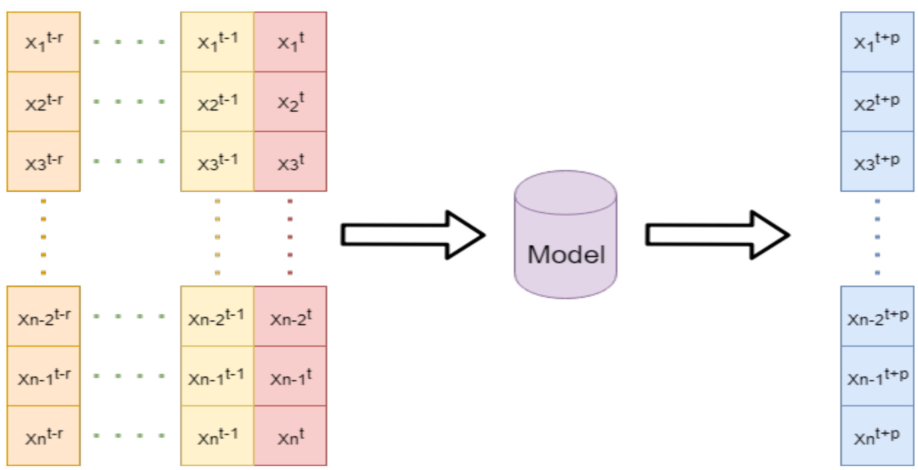


Figure 9: General Prediction Model: Base on the general model representation, we define various models for solving our problems

4.1. Daily Profile Prediction (DPP)

According to the training dataset, we compute the average flow of each station for each time points and each weekday, which means for each station, we have 7 flow curves and each curve is consisted by 480 flow values (the time interval of each time point is 3 minutes). When we make the prediction, we directly use the recorded average value as the results. This method is to set-up a base model.

4.2. Latest Flow (LF)

Secondly, we proposed another base model which makes the prediction only by the flow of current time-step. Figure 10 shows how to directly using current flow information X^t as the prediction result X^{t+q}.

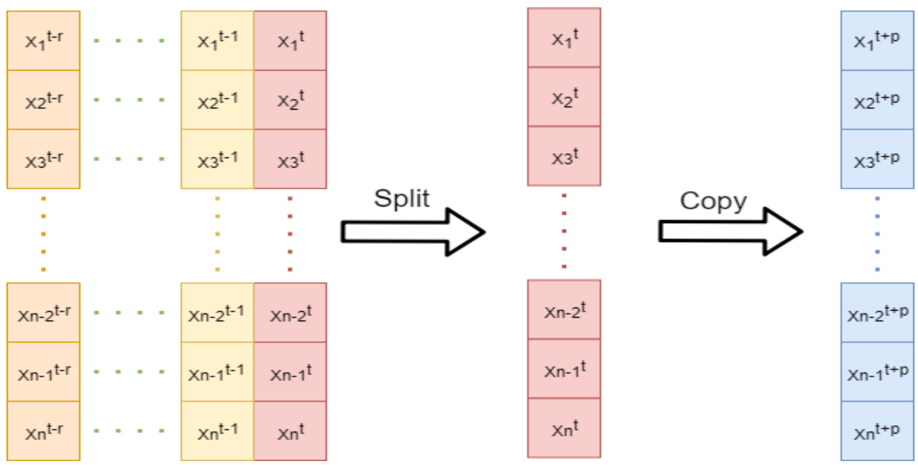


Figure 10: Directly using latest flow as a prediction model

4.3. Back Propagation Neural Network (BPNN)

Thirdly, we use a BPNN model which consists of two fully-connected layers. The input of first layers is the historical information of all selected stations and the last layers output is the prediction for all stations. BPNN is a kind of supervised neural network.

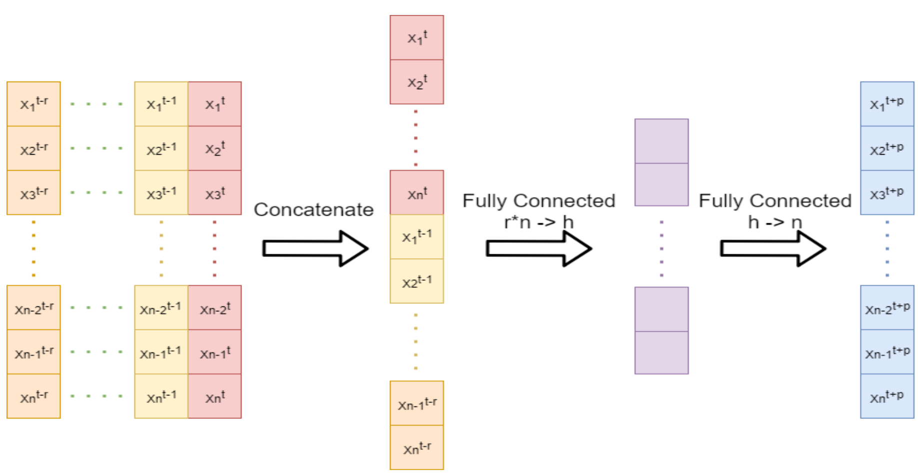


Figure 11: BPNN model

4.4. Long Short-Term Memory (LSTM)

The model is the standard model from PyTorch library. For once prediction, each time point corresponds to an input, and the output of last time point is the input of a fully-connected layers which makes the final prediction. LSTM is good at tasks about time series information and many state-of-the-art models for traffic flow prediction are based on it.

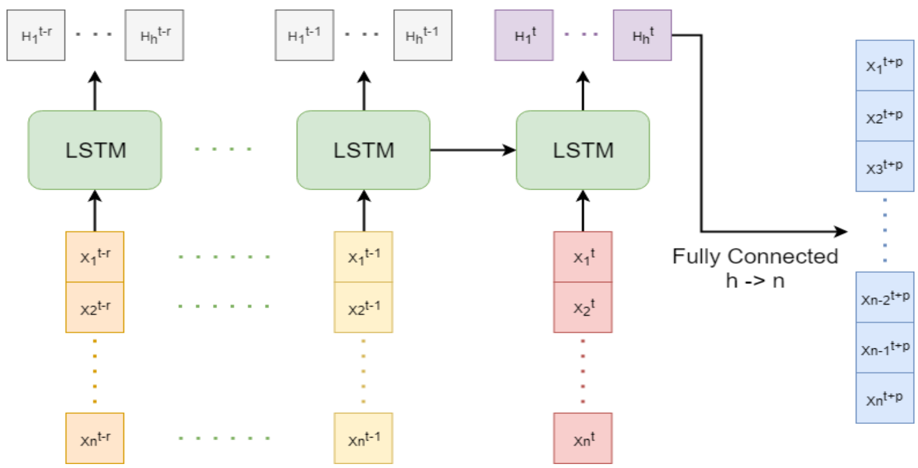


Figure 12: LSTM model

4.5. Convolutional Neural Network (CNN)

The input is the value of several previous time points of all the chosen stations which is two dimensional. After letting this input come through CNN, we resize it to a 1-dimensional feature and connect it with a fully-connected layer. Then we can get our prediction. CNN is a bio-inspired models which simulate visual signal process of human. Its performance is outstanding in many location dependent task. We apply this models since it can learn the relation between adjacent stations.

4.6. CNN-LSTM

This model is similar with LSTM. The difference is that we use a 1-dimensional filter to scan the input before the input goes into the LSTM model. The structure of LSTM can learn the connection of different time point while the structure of CNN can learn the location features. The traffic flow prediction task involves time and space dimensions, which is reason why we combine these two models together. Several other models have been considered and several research studies have been interrogated before this final choice taken in our study. These are listed in the references section [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 9, 12, 13]. The application areas of these models has been widely

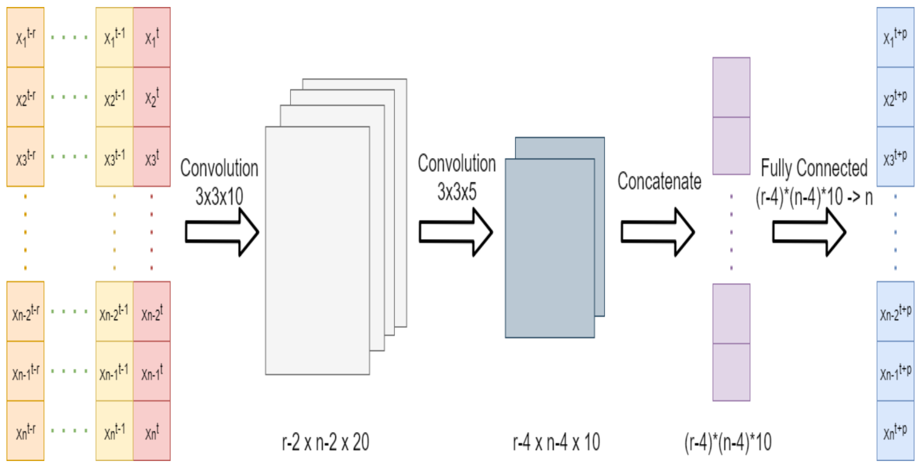


Figure 13: CNN model

adapted to multiple other traffic modelling, either independently or in combination with traffic simulation modelling, multi-agent modelling or individually [14, 4, 15, 16, 8, 17, 18, 12, 2, 19, 10, 20]. The benefits of conducting correct traffic simulation modelling can translate in improved traffic congestion, in better traffic signal control, better air quality, thus improving multiple aspects in a smart city [2, 3, 14, 21, 4, 22, 10, 13, 23, 24, 25, 20]. The methods have been widely adopted in other domains as well, as per recent works publsihed in [26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36].

5. Experiment

5.1. Data Description

In order to reduce the time of training and testing models, we only use a part of dataset. We split the dataset in two dimensions: time and space. For the aspect of time, we choose from 02-01-2017 to 03-31-2017 as the train set (28,302 time points), 04-01-2017 to 04-14-2017 (6,720 time points) as the validation set and 04-15-2017 to 04-30-2017 as the test set (7,680 time points). For training the model in a continuous way, we use all the data throughout the day (24 hours). For the aspect of space, we choose all stations in one direction (from north to south of Sydney) and there are 104 stations, including normal stations, entrance stations and exit stations.

To measure the performance of our prediction models, we calculate root mean square error (RMSE). It is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|X_i - \hat{X}_i\right|}$$

where n is the number of stations, X_i and $\hat{X}_i$ are the real and predicted flow for a station i.

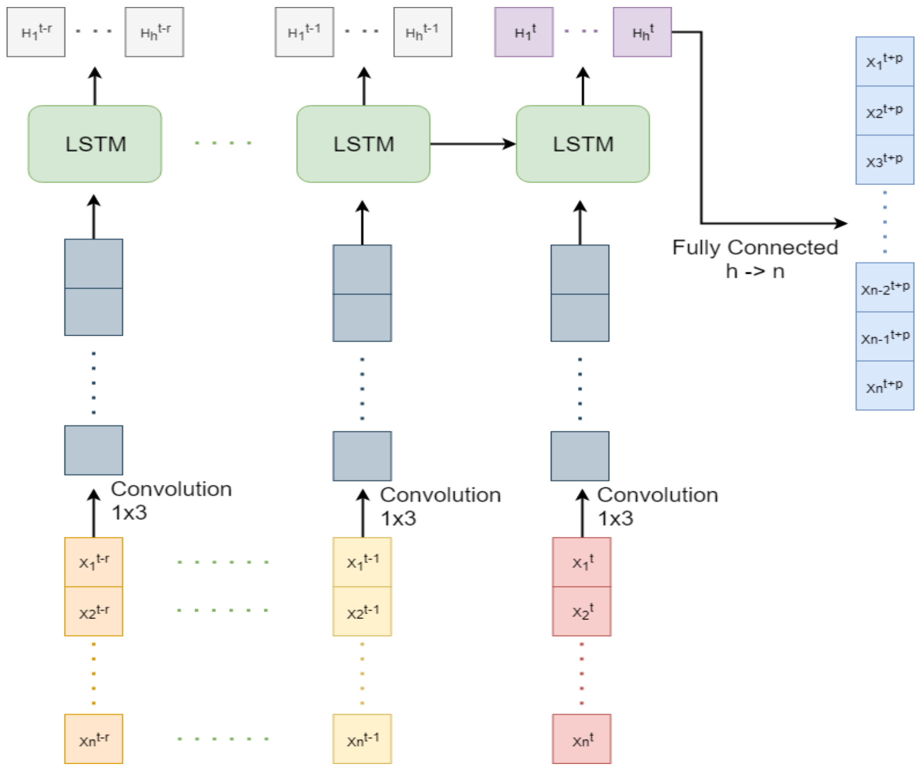


Figure 14: CNN-LSTM model

5.2. Experiment Design

For all models, we use the Adam optimizer with 3e-4 learning rate. We halt the training when the accuracy of validation set cannot decrease for 3 epochs.

Since the traffic flow value is usually several thousand and the parameters are usually less than one, for better activating the neurons, we need to normalize the traffic flow value. Thus, to normalize the flow value, all the flow value will be divided by 5,000 to make most of the traffic flow to be less than one before they are sent into model. We find the normalization can considerably improve the performance of LSTM as well as CNN and save the convergence time.

According to our attempts, neither the size of hidden units of BPNN and LSTM nor the number of kernels used in CNN can affect the accuracy remarkably. Therefore, we keep some hyper-parameters of tested models fixed: the size of the hidden units of both BPNN and LSTM is 300. For CNN, after testing different kernel sizes, finally we use 10 3*3 kernels to do the first convolution and 5 3*3 kernels to do the second convolution.

Our experiment focuses on the effect of parameter r and p and the performance of different models. The parameter r affects how many information the models are given and when the parameter p becomes larger, the prediction task will be more complicated. By comparing the performance of our different models with different r and p, we can know their ability to process time-dependent and spatial correlation information. For each hyper-parameter choice, we repeat the training 3 times.

5.3. Result

We test each model with different combinations of r and p. More precisely, we choose r from [5, 10, 15, 20] which corresponds to real time interval [15 min, 30 min, 45 min, 1 hour], and p from [1, 2, 5, 10] which corresponds to [3 min, 6 min, 15 min, 30 min].

The table below is the RMSE loss for varies choices of r, p and different models. Noticing that DPP baseline is r and p independent and LF baseline is r independent.

r	p	DPP	LF	BPNN	LSTM	CNN	CNN-LSTM
1	1	316.0	226.3	127.7	-	-	-
	2		227.2	158.9	-	-	-
	5		244.5	192.2	-	-	-
	10		275.6	214.9	-	-	-
5	1		226.3	130.4	124.0	120.4	124.3
	2		227.2	158.5	154.0	156.5	155.1
	5		244.5	189.0	186.1	186.2	189.5
	10		275.6	206.1	202.8	208.2	207.3
10	1		226.3	134.7	120.9	124.3	123.5
	2		227.2	159.4	155.0	156.2	156.5
	5		244.5	188.6	185.1	187.0	190.3
	10		275.6	204.2	201.4	206.3	205.4
15	1		226.3	138.6	121.4	128.0	123.8
	2		227.2	166.8	154.6	158.4	157.8
	5		244.5	190.0	186.3	187.4	187.4
	10		275.6	205.0	200.3	202.6	204.4
20	1		226.3	137.2	122.8	129.2	123.8
	2		227.2	165.0	155.2	159.3	160.1
	5		244.5	192.6	185.2	188.6	188.2
	10		275.6	204.3	201.3	203.6	204.6

Table 1: Performance of Different r and p Combinations on stations in way A

As we expected, every model is much better than two baselines. For Historical Average, the reason should be HA cannot consider the outliers, such as public holidays and accidents. If we use daily profile of normal days to predict public holidays which has lower traffic flow than usual, the accuracy will slump. For Latest Flow, its loss increases rapidly when p increases, since the value will be changed by time but it still uses same flow value to make prediction.

We can find that LSTM achieve best performance in almost all situation. When p=1, its accuracy is very close to CNN which has lowest loss. But when the value of p increases, the LSTM obviously outperform other models.

Another finding is that from intuition, if we make long-term prediction (more than 15 minutes, correspond to $p \geqslant 5$), we should feed the model with more historic information. However, if r becomes large, for example, we use 1 hour's historical information ($r = 20$), the accuracy of all models decreases, which means we should find a suitable r when fine-tuning our models in future research.

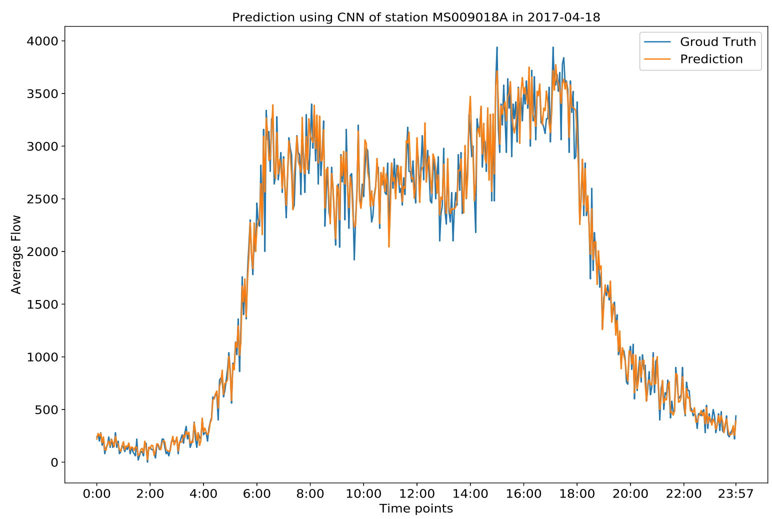


Figure 15: The prediction of CNN for station MS009018A in 2017-04-18 when $p = 1$ and $r = 5$

From this figure, we can find that the CNN model makes precise predict for almost every traffic flow fluctuations. However, if we increase p to 5, the accuracy of prediction will descend significantly. In most of time, its predictions are not precise enough to catch the peak and bottom, which may be caused by flow's frequent fluctuation. Besides, in some time, it makes totally wrong prediction. For example, around 18:00, the model makes a drop prediction when there should be a peak.

6. Conclusion

Our work makes a preliminary research on the given traffic flow information. We find that the dataset has a lot of defects and we propose some methods to solve them. Then, we test some well-known models, such as BPNN, LSTM, CNN, on selected dataset. The experiment shows LSTM outperforms other methods in most cases, but the different of their performance is slight.

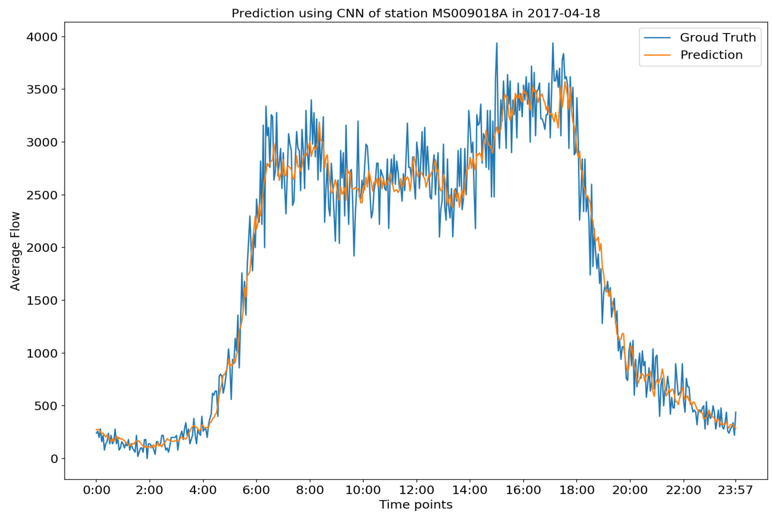


Figure 16: The prediction of CNN for station MS009018A in 2017-04-18 when $p = 5$ and $r = 5$

7. Future Work

1. It is meaningful that having more insight into the dataset. More specifically, the dataset not only has missing data, but also has many zero-values and extremely large outliers (more than 70,000). Our method to complete missing dataset is from intuition and there should be better ways.
2. In current experiment, the prediction of $P > 1$ is made in one step. Alternatively, we can make the prediction step by step. For example, if we want to predict the traffic flow at next 15 minutes, we can firstly predict traffic flow at next 3 minutes and use the result in next prediction. Repeat these two steps until we make the prediction of next 15 minutes.
3. Fitting the residual between prediction and ground true instead of the ground true itself.
4. Applying more loss functions than current one, such as Mean Absolute Percentage Error (MAPE).
5. Training models for each weekdays and the holidays.
6. Providing extra information to models may make performance improvement. We make an attempt that adding pre-processed weather, public holiday and traffic accidents information. But the performance even decreases. Our explanation is this information can only describe a day, but the prediction is made for next minutes.
7. Replacing our Adam optimizer with other more powerful optimize or fine-tune some hyper-parameter may enhance the accuracy.

8. Using more powerful baseline, such as Autoregressive Integrated Moving Average model (ARIMA).

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