

Fusion Recurrent Neural Network

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ABSTRACT

Considering deep sequence learning for practical application, two representative RNNs – LSTM and GRU may come to mind first. Nevertheless, is there no chance for other RNNs? Will there be a better RNN in the future? In this work, we propose a novel, succinct and promising RNN – Fusion Recurrent Neural Network (*Fusion RNN*). *Fusion RNN* is composed of Fusion module and Transport module every time step. Fusion module realizes the multi-round fusion of the input and hidden state vector. Transport module which mainly refers to simple recurrent network calculate the hidden state and prepare to pass it to the next time step. Furthermore, in order to evaluate *Fusion RNN*'s sequence feature extraction capability, we choose a representative data mining task for sequence data, estimated time of arrival (ETA) and present a novel model based on *Fusion RNN*. We contrast our method and other variants of RNN for ETA under massive vehicle travel data from DiDi Chuxing. The results demonstrate that for ETA, *Fusion RNN* is comparable to state-of-the-art LSTM and GRU which are more complicated than *Fusion RNN*.

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DEEPPATIAL 2020, August 24, 2020, San Diego, California, CA

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ACM ISBN 978-1-4503-XXXX-X/18/06...\$15.00

<https://doi.org/x>

KEYWORDS

Recurrent neural network, sequence learning, spatiotemporal data mining

ACM Reference Format:

Yiwen Sun, Yulu Wang, Kun Fu, Zheng Wang, Changshui Zhang, and Jieping Ye. 2020. Fusion Recurrent Neural Network. In *Proceedings of 1st ACM SIGKDD Workshop on Deep Learning for Spatiotemporal Data, Applications, and Systems (DEEPPATIAL 2020)*. San Diego, California, CA, 8 pages. <https://doi.org/x>

1 INTRODUCTION

How to extract semantic information and analyze pattern of sequence data? It is one of the most significant question of sequence learning. Since 1982, recurrent neural network (RNN) have answered this question step by step though a series of developments[6, 12, 17, 19, 20]. Time series data contains complex temporal dependency which is the important semantic information worth extracting. As a representative deep neural network, RNN is adept in extracting time series features automatically from massive data. Additionally, RNN is currency and flexible enough to handle sequence data from various fields, such as natural language processing[31], intelligent transportation system[18] and finance[22].

Early RNNs are Simple recurrent networks, Jordan networks[20] and Elman networks[12] which capture temporal correlation through recurrent structure. Though alleviating the gradient vanishing and exploding problem, Long Short-Term Memory Network (LSTM)[17] and Gated Recurrent Unit (GRU)[6] become state-of-the-art. For LSTM, there are three gates – the input gate, forget gate, output

gate and a memory cell in each inference time step. GRU adopt just two gates and do not adopt the memory cell leading to a simpler structure.

However, the necessity of gates for controlling the information flow is worth discussing. We understand that in essence, gates are to realize the effective interaction between the input and the hidden state, so that the hidden state after training contains the semantic information of the input sequence. A more concise and efficient way of information fusion between the input and the hidden state may lead to a next-generation RNN. Therefore, in this paper, we propose an RNN without any gate and memory cell structure, called Fusion RNN.

The most obvious characteristic of *Fusion RNN* is simplicity but effectiveness. *Fusion RNN* has two intuitive and clear modules – Fusion module and Transport module. For the specific sequential learning task, ETA, a representative spatiotemporal data mining task, is adopted to demonstrate *Fusion RNN*'s excellent sequential pattern analysis ability.

The main contributions in this work is included:

- We propose a novel RNN, *Fusion RNN*. *Fusion RNN* is a succinct and promising RNN in which all gate and memory cell structures are abandoned. Through quantitative calculation, we show that *Fusion RNN* is simpler than LSTM and GRU.
- For evaluating the feature extraction capability of *Fusion RNN*, we present a novel deep learning model based on *Fusion RNN* for ETA that is important data mining task. This deep learning model's core sequence feature extraction module of this model can be replaced by any RNN to ensure fair comparison.
- We train and test our method on the large-scale real-world dataset whose trajectory number is over 500 million. The experimental results validate that for ETA *Fusion RNN* shows competitive sequence feature extraction ability compared with LSTM and GRU.

We organize this paper's rest part as follows. Section 2 summarizes the related works of sequence learning as well as recurrent neural network. Section 3 introduces the structure of our *Fusion RNN*, followed by the deep learning model based on *Fusion RNN*. In Section 4, the experimental comparisons on the real-world datasets for ETA are presented to show the superiority of *Fusion RNN*. Finally, we conclude this paper and present the future work in Section 5.

2 RELATED WORK

In this section, we briefly introduce works on sequence learning, recurrent neural network and estimated time of arrival.

2.1 Sequence Learning

A large amount of things in life are related to time, which means many living materials are stored in the form of sequence, such as text, speech and video. In order to flexibly handle sequence data of different lengths and extract useful information effectively, sequence learning [9, 10, 14, 34, 42] has become one of the hot spots of machine learning in recent years. It is widely used in recommendation systems [45], speech recognition [4, 5, 11, 41], natural language processing [7, 35, 36, 43], intelligent transportation system

[13, 40] and other fields. In early works people use support vector machines[2], autoregressive model[29], hidden Markov models[33] and so on to learn features from sequence. With the increase in the amount of data and the great development of deep learning[21, 23–25], deep neural networks [28, 39] have become an effective way to solve sequence learning problems. Among the deep learning methods, recurrent neural network (RNN) is the most effective solution to sequence learning[27].

2.2 Recurrent Neural Network

Recurrent neural network (RNN) is a type of network that takes serial data as input with the ability to selectively pass information across sequence steps. In 1982, Hopfield[19] first proposed a recurrent neural network, which has pattern recognition capabilities. Elman[12] and Jordan [20] improved RNN and their networks are known as “simple recurrent networks” (SRN). Since then researchers continued to make improvements in recurrent neural network [6, 8, 15, 17, 26, 44]. The most classical RNN algorithms are two closely related variants of RNN, Long Short-Term Memory Network (LSTM)[17] and Gated Recurrent Unit (GRU) [6]. Both LSTM and GRU can carry valuable information for a long sequence, solve the problem of gradient disappearance and gradient explosion in the traditional RNN, and perform well on tasks with long sequences. However, several gates have been used in both GRU and LSTM structures, which greatly improve the complexity of the model. Our model which simply carry interactive operations between input vectors and hidden states doesn't add additional gates into a cell. We can achieve a better performance than LSTM and GRU in the sequential learning task with a simpler structure.

2.3 Estimated time of arrival

Estimated time of arrival (ETA) is one of the difficult problems in sequence learning, which refers to the process of estimating the travel time when given departure, destination and the corresponding route. It is a challenging problem in the field of intelligent transportation system. There are two category methods to solve the problem, route-based method and data-driven method. The route-based method focus on estimating the travel time in each individual link which is split from the original whole route. Traditional machine learning methods such as dynamic Bayesian network [18], gradient boosted regression tree [48], least-square minimization [47] and pattern matching[3] are typical approaches to capture the temporal-spatial features in the route-based problem. However, a drawback of this method is the accumulation of local errors brought by the split operation.

The data-driven method is popular both in academia and industry. As the advance of deep learning[23, 24], this category method has shifted from early traditional machine learning methods such as TEMP[38] and time-dependent landmark graph[46] to deep learning methods. Deeptravel[49] converts the travel trajectory into a grid sequence, and learns the time interval between the origin and the destination to the intermediate point simultaneously through BiLSTM. DeepTTE[37] adopts proposed geo-convolution and standard LSTM to estimate the travel time through raw GPS points. WDR[40] proposes a joint model of wide linear model, deep neural

network and recurrent neural network, which can effectively capture the dense features, high-dimensional sparse features and local features of the road sequence. Most data-driven methods use LSTM for time series' learning but the LSTM model is slow on large-scale data sets. So it's vital to further simplify the LSTM model and retain its good performance in ETA.

3 METHOD

In this section, we introduce the architecture of *Fusion RNN* and its application in estimated time of arrival (ETA).

3.1 Fusion RNN

Gated recurrent neural network[6] has achieved promising results in many sequence learning tasks. It uses several gating units to control the transfer process of information in the network. LSTM [17] is one of the most widely used RNN algorithms because of its excellent performance especially on long sequence tasks. However, LSTM adds three gated units, an input gate, an output gate and a forget gate, on the basis of simple recurrent networks. The gates greatly increased the amount of model parameters and the computational complexity. GRU's structure is like LSTM but has fewer parameters than LSTM, as it lacks an output gate. GRU's performance on certain tasks of polyphonic music modeling and speech signal modeling was found to be similar to that of LSTM. GRU have been shown to perform better performance than LSTM on some smaller datasets[8]. However, GRU still has two gates, the reset gate and the update gate. Is gated unit the only option for RNN to achieve good performance? Can we use a recurrent neural network without gated units to achieve similar performance in sequence learning tasks? To solve this problem, our strategy is to directly make changes on the architecture of simple recurrent networks. We propose a novel recurrent neural network, *Fusion RNN*, without any gated unit. We achieve a similar performance with LSTM and GRU on sequence learning tasks through a very simple interactive operation structure. We will discuss *Fusion RNN* in detail next.

As shown in Figure 1, the large black box in the upper part of the figure represents one time step, and the hidden state parameter h_t of the next time step should be calculated by the input x_t and the hidden state h_{t-1} of the previous time step. As for how to calculate h_t and how to control the information flow, there are different designs in different recurrent neural networks. For example, Elman network uses a simple recurrent unit while LSTM uses three gates in each time step. We think that the most important thing is the fusion of input information and the hidden state information and the calculation of h . So we designed two modules in our *Fusion RNN*, Fusion module and Transport module. The Fusion module is a process of multi-round interactive fusion of input vector x_t and the hidden state vector h_{t-1} . The purpose of the fusion process is make the final input vector x_t^r contains information of h_{t-1} , and the final hidden state h_{t-1}^{r-1} contains information of x_t . We refer to [30] for the mogrifier operation of input vector x_t and the hidden state parameter h_{t-1} between each time step. We don't add the hyperparameter 2 to our Fusion module's formula so that the model is easier to converge. This makes our proposed structure more essential and significant. Full fusion of features is the foundation

Table 1: The amount of parameters in different RNN models.

	$m \neq n$	$m = n$
LSTM	$4mn + 4n^2 + 4n$	$8n^2 + 4n$
GRU	$3mn + 3n^2 + 3n$	$6n^2 + 3n$
Fusion RNN	$n^2 + 3mn + n$	$4n^2 + n$

¹ m is the input size and n is the hidden size.

Table 2: Multiplication times of one recurrent cell.

	$m \neq n$	$m = n$
LSTM	$4mn + 4n^2 + 3n$	$8n^2 + 3n$
GRU	$3mn + 3n^2 + 3n$	$6n^2 + 3n$
Fusion RNN	$n^2 + (1 + r)mn + ([r/2])n + ([r/2] + 1)(m)$	$(r + 2)n^2 + rn$

¹ $[.]$ is the floor function, r is the number of interaction iterations in Fusion module, m is the input size and n is the hidden size. The length of sequence l is suppose to be 1. Otherwise, all items in this table should be multiplied by l .

of the Transport module. The Transport module is a recurrent unit in which the current hidden state h_t is calculated. We concatenate the input x_t and the previous hidden state h_{t-1} together, and use a feed forward network to extract features based on the simple recurrent network, Elman network. Here we select tanh function as the activation function. Then the current hidden state h_t is passed to the next time step.

In order to intuitively reflect the simplicity of our model, we compare the parameters of Fusion RNN with LSTM and GRU models. We can see from table1 that our model have fewer parameters than GRU and LSTM. *Fusion RNN*'s amount of parameters is $n^2 + 3mn + n$, $2n^2 + 2n$ less parameters than GRU and $3n^2 + mn + 3n$ less parameters than LSTM when $m \neq n$. *Fusion RNN*'s amount of parameters is $4n^2 + n$, $2n^2 + 2n$ less parameters than GRU and $4n^2 + 3n$ less parameters than LSTM when $m = n$. The interactive operation in Fusion module is calculated by Formula 1 and Formula 2, the recurrent unit in Transport module is calculated by Formula 3:

$$x_t^i = \sigma \left(F^x h_{t-1}^{i-1} \right) \odot x_t^{i-2}, \quad \text{for odd } i \in [1 \dots r] \quad (1)$$

$$h_{t-1}^i = \sigma \left(F^h x_t^{i-1} \right) \odot h_{t-1}^{i-2}, \quad \text{for even } i \in [1 \dots r] \quad (2)$$

$$h_t = \tanh \left(W^x x_t + W^h h_{t-1} + b \right) \quad (3)$$

where x_t is the input vector, h_{t-1} is the hidden layer vector, y_t is the output vector, W^x , W^h is weight, b is bias, r is the number of iterations, F^* are learned parameters, tanh is the tanh function, and σ is the activation functions. The activation functions commonly used in RNN are sigmoid function and tanh function. Here we use tanh function as activation function in Fusion module.

Here m is the input size and n is the hidden size and usually $m < n$. The results shows that our *Fusion RNN*'s training time is shorter and the model size is smaller than other gate-based recurrent neural networks which means that our model is more convenient to application.

We have iterative interactive operations in *Fusion RNN*. Considering the effect of iterations on the model's inference speed,

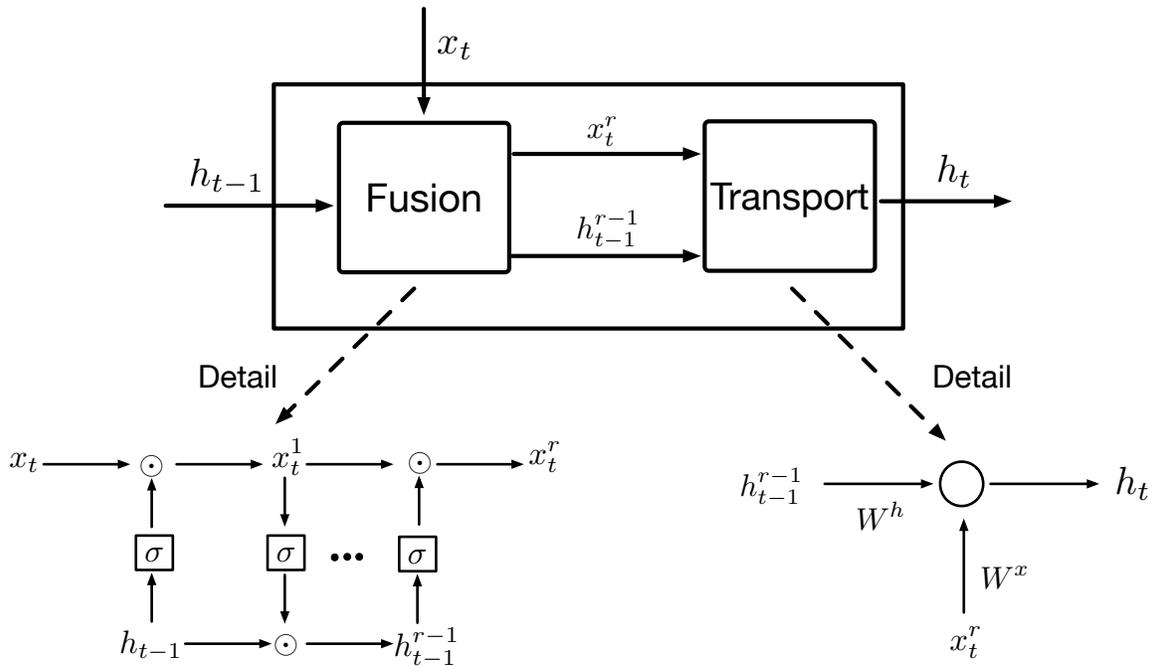


Figure 1: The architecture of Fusion RNN. Information in the input vector and the hidden state vector interact in the Fusion module which is shown in the bottom left part of the figure. Here the number of iterations r is odd. The Transport module is a basic recurrent unit which is shown in the bottom right part of the figure.

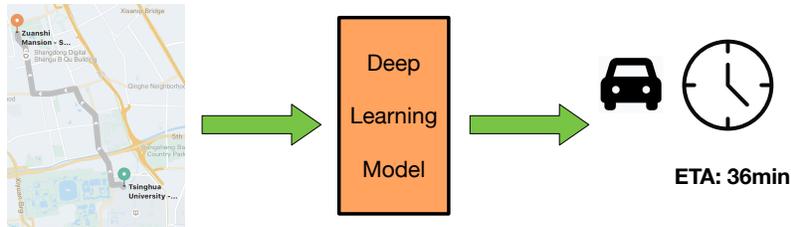


Figure 2: The conceptual sketch of deep learning based ETA. ETA is the travel time along the given path for a specific vehicle. A deep learning model is adopted for automatic extraction of semantic features from mass data.

we compared the multiplications times of one recurrent cell in different RNN algorithms. The results are shown in Table 2. Here the length of sequence l is supposed to be 1. Otherwise, all items should be multiplied by l . *Fusion RNN*'s amount of parameters is $n^2 + (1+r)mn + ([r/2]n + ([r/2] + 1)(m))$ when $m \neq n$ and $(r+2)n^2 + rn$ when $m = n$. The multiplication times of *Fusion RNN* depend on the number of iterations r , which is usually set between 1 and 5. From the table 2 we can learn that when r is less than 4, *Fusion RNN* has fewer multiplication times than GRU and when r is less than 6, *Fusion RNN* has fewer multiplication times than LSTM. The result shows that in general, *Fusion RNN* is more concise than LSTM which means our model's inference speed is faster than LSTM. Experiments in Section 4 show that our *Fusion RNN* performs well in sequence learning. Our *Fusion RNN* outperforms GRU and performs a little better than LSTM. The detail will be discussed in Section 4.

Our *Fusion RNN* only uses three formulas. Its amount of parameters and computational complexity are less than LSTM. That is, we successfully propose a simpler recurrent neural network whose performance is close to or even better than LSTM without using any gated unit.

3.2 FusionRNN-ETA

Estimated time of arrival (ETA) is the process of estimating the arrival time based on departure, destination and trajectory information. Figure 2 shows an example of ETA and one of the practical applications of ETA. It is one of the most basic and essential tasks in the intelligent transportation system and one of the representative tasks of sequence learning based on spatio-temporal data. We test the performance of *Fusion RNN* on ETA problem and propose a FusionRNN-ETA model. Wang et al. modeled ETA as a regression

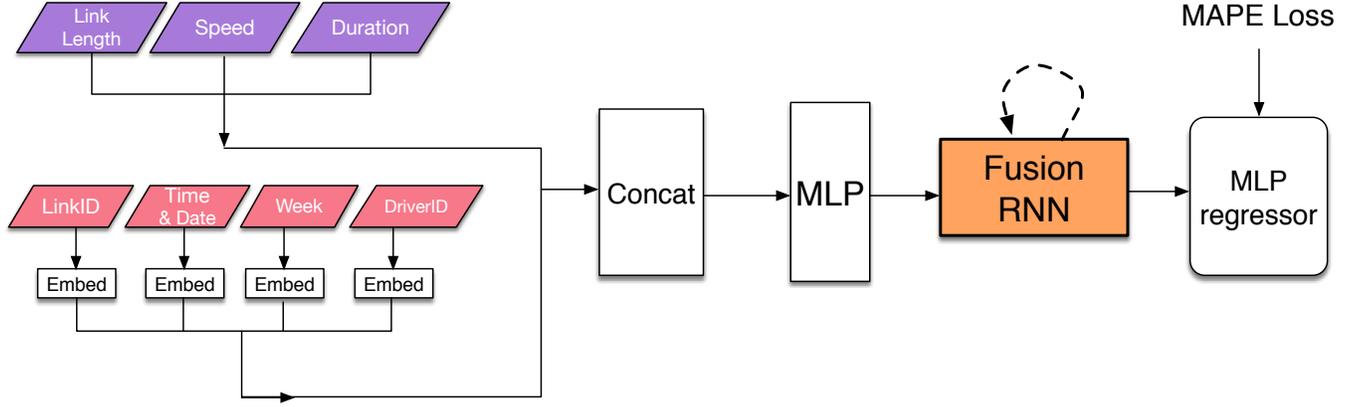


Figure 3: The architecture of FusionRNN-ETA. Spatial features are concatenated with sequential features after embedding layer. After the MLP module, features enter the feature extractor Fusion RNN. Finally, we perform regression on the extracted features.

learning problem. We then give the definition of ETA learning problem which is essentially a regression task:

Definition 3.1 (ETA learning). For a track order from massive data $D = \{s_i, e_i, d_i, \mathbf{p}_i\}_{i=1}^N$, s_i is i -th trak departure time, e_i is i -th trak arrival time, d_i is the driver ID, \mathbf{p}_i is the road segment sequence set of the order. \mathbf{p}_i is represented as $\mathbf{p}_i = \{l_{i1}, l_{i2}, \dots, l_{iT_i}\}$, where l_{ij} is the j -th link of i -th trajectory, and T_i is the length of the link sequence set. N is the total sample number of the dataset. We computed the ground truth travel time by $y_i = e_i - s_i$. Our objective is to train a machine learning model which could estimate the travel time y'_i when the departure time, the driver ID and the route are given.

3.2.1 Data Preprocessing. We first construct a rich feature set from the raw information of trips. The original data in the dataset of ETA tasks is made up of the departure’s and destination’s latitude and longitude, the time stamp, driver ID, and GPS points of the trajectory. We convert the time stamp to date, day of the week and specific departure time. We divide the day into 288 5-minutes time slices. Then we carry map matching [32] algorithm on the GPS trajectory to obtain a set of road links corresponding to the set of GPS points. We use historical trajectories in adjacent previous time to estimate the road conditions. After the process, the features can be categorized into two kind of types:

(1) The non-sequential features which are irrelative to the travel path, such as time and driver ID.

(2) The sequential features extracted from the link sequence set \mathbf{p}_i . For j -th link l_{ij} in \mathbf{p}_i , we denote its feature vector as x_{ij} and get a feature matrix X_i for the i -th trip. The features in x_{ij} is the basic information of the selected link, e.g. length and speed.

3.2.2 Overall framework. We desire to adopt our Fusion RNN to ETA problem. We choose the state-of-the-art Wide-Deep-Recurrent (WDR) model [40] as our basic model to solve the problem. The three components of WDR model includes: (1) A wide module uses a second-order cross product and affine transformation of the non-sequential feature z_i to memorizes the historical patterns; (2) A

deep module constructs embedding table[1] for the sparse discrete features in sequence. The embedding vectors are concatenated, then they are put into a Multi-Layer Perceptron (MLP), which is a stacked fully-connected layers with ReLU[21] activation function; (3) A recurrent module integrates the sequential features together and inputs these features into a fine-grained RNN-based model which can capture the spatial and temporal dependency between links.

We simplify and further improve the structure of WDR and develop a novel ETA model FusionRNN-ETA based on our *Fusion RNN* which have interactive operation between the input vector and the hidden state parameter in each time step. We remove the wide module of WDR. The principles of *Fusion RNN* have been explained in detail in Section 3.1. Next, we will introduce the overview of our model and describe all components in detail. A description of the overall the architecture of FusionRNN-ETA is given in Figure 3. We remove the wide module in WDR and directly use deep module to extract sequential and non-sequential features. We use embeddings on link ID and non-sequential features. The embedding vector is an important component of these features. For example, for a link with ID l_{ij} , we look up an embedding table[1] $E_L \in \mathbb{R}^{20 \times M}$, and use its l_{ij} -th column $E_L(:, l_{ij})$ as a distributional representation for the link. We perform the same embedding operation on the non-sequential features.

Next we concatenate the embedding features with the sequential features. Then we put the concatenated features into a MLP which is a stack of fully-connected layers with RELU activation function. The output features after MLP are feed into a recurrent module. We use *Fusion RNN* as the recurrent neural network algorithm in the recurrent module. The travel time prediction is given by a regressor, which is also a MLP, based on the outputs of *Fusion RNN*. The hidden state sizes in *Fusion RNN* and the regressor MLP are all set to 128. The hidden state of *Fusion RNN* are initialized as zeros.

The parameters of the FusionRNN-ETA are trained by optimizing the Mean Absolute Percentage Error (MAPE) loss functions:

$$\text{MAPE} = \frac{1}{N} \sum_{j=1}^N \frac{|y_j - y'_j|}{y_j} \quad (4)$$

where y'_j is the predicted travel time, y_j is the ground truth travel time.

4 EXPERIMENT

4.1 Dataset

The dataset used in our experiment is the massive real-world floating-car trajectory dataset provided by the Didi Chuxing platform. It contains the trajectory information of Beijing taxi drivers for more than 4 months in 2018, so we call this dataset Beijing 2018. The dataset is huge and the numbers of unique links are very large. These road-segments contain a variety of complicated types, for instance, local streets and urban freeways. Before the experiment, we filtered the anomalous data whose travel time less than 60s and travel speed greater than 120km/h. We divided this data set into a training set (the first 16 weeks of data), a validation set (the middle 2 weeks of data) Test set (data for the last 2 weeks).

4.2 Compared Methods

We compare our FusionRNN-ETA with 6 route-based, linear-based, and RNN-based models on the massive real-world datasets. We select route-ETA as the representation of traditional method. It has vety fast inference speed but its accuracy is often far from satisfactory compared with deep learning methods. We choose an improved version of WDR which is illustrated in Section 3.2 as the representative of deep learning methods. We apply different RNN algorithms on the recurrent module of the deep model or use other deep models such as FFN and resnet to replace the recurrent module.

(1) Route-ETA: a representative method for non-deep learning methods. It splits a trajectory into many links. The travel time t_i in the i -th link in this trajectory is calculated by dividing the link's length by the estimated speed in this link. The delay time c_j in the j -th intersection is provided by a real-time traffic monitoring system. The final estimated time of arrival is the sum of all links' travel time and all intersections' delay time.

(2) FFN: an artificial neural network where the connections between each nodes don't form a cycle. Here we use a Multi-Layer Perceptron network for comparison.

(3) Resnet[16]: a deep convolutional neural network with residual structure. It explicitly reformulate the layers as learning residual functions with reference to the layer inputs [16]. Here we use a shallow simplified version to extract features.

(4) RNN: an artificial neural network which takes sequence data as input and recurs in the direction of sequence. The connections between nodes form a directed graph along the temporal sequence. Here we use Elman network [12] as RNN algorithms.

(5) GRU [6]: a specific recurrent neural network with a gating mechanism. GRU has two gates, the reset gate and the update gate.

Table 3: The results of different sequence pattern analysis methods

	MAPE(%)	MAE(sec)	RMSE(sec)
Route-ETA	25.010	69.008	106.966
FFN	21.106	57.797	93.588
Resnet	21.015	57.064	92.241
RNN	19.677	55.284	90.836
GRU	19.673	55.372	90.801
LSTM	19.598	55.227	90.480
Fusion RNN (ours)	19.579	55.019	90.289

(6) LSTM [17]: a specific recurrent neural network with three gates, an input gate, a forget and an output gate on the basis of simple recurrent networks.

4.3 Experimental Settings

In our experiment, all models are written in PyTorch and are trained and evaluated on a single NVIDIA Tesla P40 GPU. The number of iterations of the deep learning-based method is 3.5 million, and the batch size is 256. FusionRNN-ETA's number of iteration is r ($r \text{ in } [1, 5]$). We use the method of Back Propagation (BP) to train the deep learning-based methods, and the loss function is the MAPE loss. We choose Adam as the optimizer due to its good performance. The initial learning rate is 0.0002.

4.4 Evaluation Metrics

To evaluate and compare the performance of FusionRNN-ETA and other baselines, we use three popular criterions, Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE) and Rooted Mean Square Error (RMSE):

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - y'_i| \quad (5)$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - y'_i)^2} \quad (6)$$

where y'_j is the predicted travel time, y_j is the ground truth travel time, and N is the number of samples. The calculation process of MAPE is shown in Section 3.1.

4.5 Comparison and Analysis of Results

As seen in the Table 3, our *Fusion RNN* outperforms all competitors in terms of all metrics on Beijing 2018 dataset. The detailed experimental results and analysis are as follows.

(1) The representative non-deep learning method, route-ETA obviously performs worse than other deep learning methods. Route-ETA is a rule-based method baseline. This result shows that the data-driven method is more effective than the artificial method in modeling complex transportation system given massive spatio-temporal data.

(2) LSTM and GRU performs better than RNN which is specifically Elman Network. Among the existing variants of RNN, LSTM performs best. This is because the introduction of gating mechanism really improves the mining ability for sequence data.

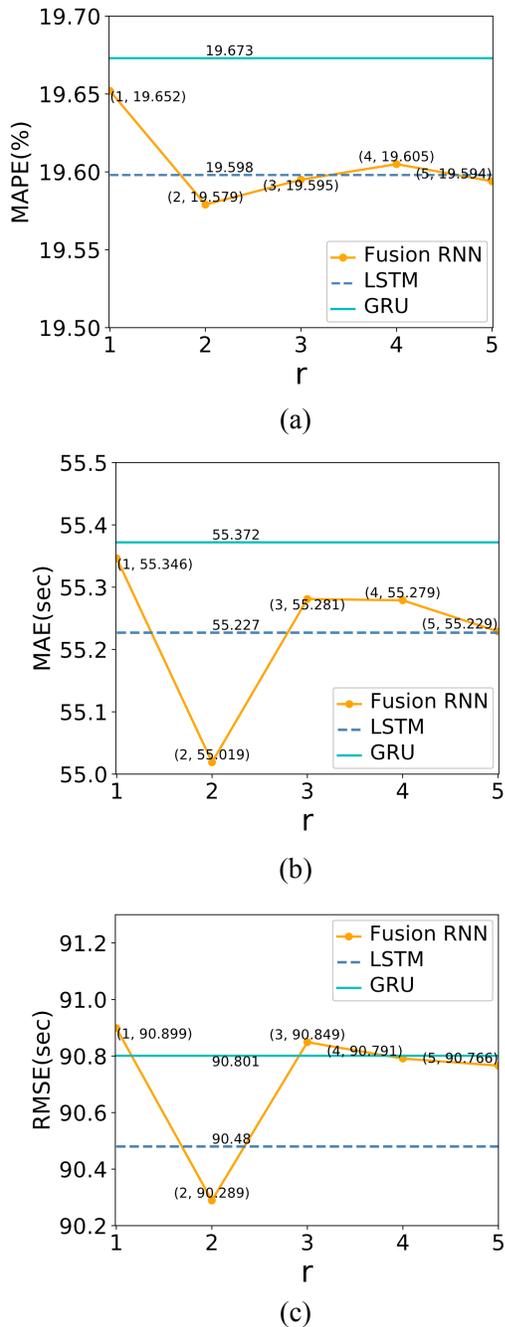


Figure 4: FusionRNN-ETA's performance under different number of iterations. (a) Comparison in terms of MAE on Beijing 2018 dataset. (b) Comparison in terms of MAPE on Beijing 2018 dataset. (c) Comparison in terms of MSE on Beijing 2018 dataset.

(3) Our *Fusion RNN* performs best for ETA and outperforms LSTM by 0.09% in terms of MAPE loss, 0.38% in terms of MAE loss and 0.21% in terms of RMSE loss.

Our *Fusion RNN* can achieve better performance with a simpler structure than LSTM suggesting that *Fusion RNN* is a promising universal sequential feature extractor.

4.6 Influence of Hyper-parameter

We explore the impact of the number of iterations in Fusion module on the model's performance, and the results are shown in Fig. As illustrated by the graphs, the following results can be summarized.

(1) No matter how the parameter r changes from 1 to 5, *Fusion RNN* is competitive compared with LSTM and GRU. This demonstrates that *Fusion RNN* is robust according to r . Furthermore, when $r = 1$ or 2, *Fusion RNN* is pretty simpler than LSTM, yet, has similar prediction effect.

(2) The superiority of *Fusion RNN* compared with LSTM and GRU is obvious when $r = 2$. This shows that the proper number of fusion rounds of input and hidden state vector is of importance for sequence semantic analysis.

5 CONCLUSION AND FUTURE WORK

In this paper, we propose a novel RNN – Fusion Recurrent Neural Network (*Fusion RNN*). *Fusion RNN* is a general, succinct and effective feature extractor for sequence data. *Fusion RNN* is simpler than state-of-the-art and popular LSTM and GRU. We conduct sufficient experiments on the large-scale real-world dataset for one representative data mining task, ETA. The evaluations show that *Fusion RNN* has competitive sequence semantic information extraction ability compared with LSTM and GRU. Evaluating and tapping the potential of *Fusion RNN* in other sequence machine learning domain, such as natural language processing and speech processing is our future work. Maybe this paper is just a small step, nonetheless, a better RNN is of great importance for the future of sequence learning.

ACKNOWLEDGMENTS

This work is funded by the NSFC (Grant No. 61876095 and 61751308).

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