Big Data Application for Network Level Travel Time Prediction

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ABSTRACT

Travel time is essential in advanced traveler information systems (ATIS). This paper used the big data analytic engines Apache Spark and Apache MXNet for data processing and modeling. The efficiency gain was evaluated by comparing them with popular data science and deep learning frameworks. The hierarchical feature pooling is explored for both between layer and the output layer LSTM (Long-Short-Term-Memory). The designed hierarchical LSTM model can consider the dependencies at a different time scale to capture the spatial-temporal correlations from network-level corridor travel time. A self-attention module is then used to connect temporal and spatial features to the fully connected layers, predicting travel time for all corridors instead of a single link/route. Seasonality and autocorrelation were performed to explore the trend of time-varying data. The case study shows that the Hierarchical LSTM with Attention (hiLSTMat) model gives the best result and outperforms baseline models. The California Bay Area corridor travel time dataset covering four-year periods was published from Caltrans Performance Measurement System (PeMS) system.

Keywords: Network Travel Time, Apache Spark and MXNet, Big Data, Hierarchical LSTM

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INTRODUCTION

Travel time is a major input in the advanced traveler information system (ATIS) used for route guidance and mode choice on freeways, urban arterials, and corridors. The continuous and updated travel time allows the traffic management center to effectively adjust their forecast of trip information for travelers. From the users' perspective, predictive travel time is used to select their routes, travel modes, and departure time based on the perception of certainties. From the system perspective, the prediction of travel time can enable traffic system engineers to evaluate beneficial gains from possible responses under different circumstances. Long-term travel time (greater than 60-minute time horizon) prediction models are usually for policy and planning and considering more static conditions, such as Origin-Destination (OD) patterns, traffic zone analysis, road capacities, land use, population, etc. Short-term travel time (less than 60-minute time horizon) prediction models are often for trip decision purpose that predicts travel time in the near future. Lint (2006) has described a good travel time prediction model should be accurate (in terms of predictive performance), robust (to cope with different conditions), and adaptive (constantly adapt parameters accordingly).

Travel time is influenced by the imbalance between traffic demand and supply, traffic control, the randomness of behaviors, as well as exogenous factors, such as the weather and accident. Travel time prediction models are classified into two types. One is a data-driven approach; the other is the model-based heuristic approach. Model-based methods estimate travel time through measurable parameters (traffic volume, occupancy, speed, social media data), including queuing theory-based models (Skabardonis and Geroliminis, 2005), Cell Transmission model (Wan et al., 2014; Seybold, 2015), dynamic traffic assignment. Model-based methods can explicitly describe the traffic process and provide insight into the causes of delay. However, model-based methods are mainly derived from principles of physics, therefore can hardly account for the randomness and inconsistency of individual travelers and relies on the information of infrastructure facility. Instead of focusing on the traffic process, data-driven models consider the traffic process as a black box and predict travel time without any behavior assumptions. Data-driven models consist of two types of models, which are pure statistical approaches
including linear regression methods (Zhang and Rice, 2003; Zhang and Haghani, 2015), ARIMA (Williams and Hoel, 2003; Smith et al., 2002), support vector regression (Castro-Neto et al., 2009; Bao et al., 2016), Kalman filter (Liu et al., 2015; Lint, 2008) and pattern recognition-based approaches (k-Nearest Neighbor Based Methods (Myung et al., 2011; Zhao et al., 2018) and State-Space Neural Network-based methods (Lint et al., 2005), Deep Learning based methods (Liu et al., 2017; Wu et al., 2018). Data-driven approaches don't require location-specific info or strong modeling assumptions, which can fit into the constantly evolving temporal data analysis techniques. Given the widely installed traffic monitoring systems that generate sufficient travel time data, the scope of this paper focuses on big data computing engines for network travel time processing and modeling. A hierarchical feature pooling was added to existing prediction model that merges LSTM hidden states from multiple timesteps for network travel time prediction. The travel time prediction results can benefit advanced traveler information systems for both commercial App and government-owned web interfaces.

To summarize, our main contributions are:

1. Big data tools were applied in the travel time prediction task. The reference and proposed models were developed with Apache Spark and Apache MXNet that are scalable computing platforms designed for big data workloads.
2. Existing travel time prediction models with LSTM as the backbone are built on stacked architecture without hierarchical feature extraction capability. We design hierarchical features module analogous to the pooling layer in Convolutional Neural Network to capture information of different time scales.
3. The self-attention module is incorporated that passes on extracted features from the LSTM layers to fully connected layers to add robustness and accuracy. Autocorrelation analysis and stationary transformation were performed to reveal the underlying properties of travel time.
4. We published a new travel time dataset, which is by far the biggest from the Caltrans Performance Measurement System (PeMS) for District 4 area (from August-1$^{st}$-2017 to Oct-31$^{st}$-2021), at a 5-min time-frequency.
RELATED WORK

The Time-series data analysis technique is ubiquitously used for modeling temporal measurements and is a key area for data science, such as stock price prediction, weather forecasting, bank transactions, decision making, and biology, to list a few. It comprises a modeling method to extract meaningful statistics from data and the use of the model to predict future data based on previously obtained values. Predicting travel time, which has only one time-dependent variable, based on its own previous value is a type of univariate forecasting problem. The univariate forecasting problem is expressed as the following equations:

Given a sequence of data points \( X = \{x_1, x_2, x_3, \ldots, x_t\} \). The prediction of travel time is the modeling of the dependence of current value with post values. Thus

\[
\{x_{t+1}, x_{t+2}, x_{t+3}, \ldots, x_{t+h}\} = F(X) + \epsilon
\]

(1)

\( F \) is the model for the univariate prediction problem with input \( X \), \( \epsilon \) is the noise, and \( h \) is the prediction horizon.

Traditional time series relies heavily on preprocessing and feature engineering, such as Hidden Markov Models (HMMs) (Cheng and Li 2011), dynamic Bayesian networks (Robinson et al., 2010), Kalman filters (Bézenac et al., 2020), and other statistical models (e.g., ARIMA). The distance-based or feature-based regression and classification models have advantages when the data volume is small compared to complex machine learning models (Bandara et al., 2020). However, most time-series data is continuously updated, resulting in a large data size. The traditional univariate time series modeling methods with a limited number of parameters need to be retrained frequently and are incapable of capturing complex patterns when dealing with the massive dataset.

In the era of big data analytics, Neural networks have achieved remarkable performance on data-driven tasks with various new architectures that can efficiently learn the representation of data according to the universal approximation theorem. The recurrent neural networks (RNN) are the go-to option for temporal series data modeling, which address limitations of the traditional time series models with automatic feature extraction capability. To avoid the notorious gradient exploding/vanishing issues, the
gated mechanism is proposed, resulting in Gated Recurrent Unit (GRU) (Chung et al., 2014) and Long-Short-Term Memory (LSTM) (Hochreiter et al., 1997). Sequence-to-sequence (Seq2Seq) architecture introduced by Sutskever et al. (2014) is another popular RNN architecture to generate variable length of sequential results from a different domain input, which is widely used in machine translation, video captioning, and speech recognition. Attention and Transformer (Vaswani et al., 2017) has been increasingly used and gained top performances on many machine-learning tasks. The attention mechanisms have been combined with Seq2Seq models to represent time series with a single vector instead of encoding all the information, showing better learning capacity with fewer parameters (Luong et al., 2015; Abdelraouf et al., 2021). The deep learning based approaches go beyond the univariate forecasting that output network scale travel time prediction (Hou and Edara, 2018).

**Multiscale Hierarchical Modeling**

Multiscale information is important for spatial and temporal data modeling and has been proved as a successful approach for temporal data analysis. The hierarchical deep neural networks are commonly used for image recognition tasks (Jacobsen et al., 2017). Inspired by the success of image science, researchers have tried similar approaches for time series data modeling, and many results have shown great benefits by employing multiscale temporal features for efficient temporal modeling tasks. Wehmeyer and Noé (2018) developed time-lagged autoencoders to perform the dimension reduction that captures the slow dynamics of the underlying stochastic processes for molecular kinetics. The Temporal Shift Module (TSM) was proposed by Lin et al. (2019) for hardware-efficient video streaming understanding. TSM model has three main advantages: low latency inference, low memory consumption, and multi-level fusion. Liu et al. (2020) developed the multi-resolution convolutional autoencoder (MrCAE) architecture to model the Spatio-temporal dynamics using a progressive-refinement strategy. Li et al. (2020) proposed the MS-TCN++ (Multi-Stage Temporal Convolutional Network for Action Segmentation) to address the over-segmentation errors for action segmentation in video analytics with temporal convolution and temporal
pooling approaches. Kahatapitiya and Ryoo (2021) developed a two-stream architecture named Coarse-Fine Networks, which benefits from different abstractions of temporal resolution to learn better video representations for long-term motion. Chu, Lam, and Li (2020) have implemented a multiscale convolutional LSTM network (MultiConvLSTM) for travel demand and Origin-Destination predictions. Their experiments on real-world New York taxi data have shown that the MultiConvLSTM considers both temporal and spatial correlations and outperforms the existing methods.

**Travel Time Prediction Models**

A plethora of literature bodies on short-term travel time prediction have been developed using model-based, simulation, or historical detector data. Historical database approaches give the current and future travel time according to the previous record, assuming the travel time on road segment follows the same pattern on workdays and non-workdays, based on the hypothesis that similar individuals travel on a similar route from origin to destination. the historical data-based approaches are often used with other models to make long-term predictions. Time series models are the commonly used approaches, including autoregressive (AR), moving average (MA) models, ARIMA model (which is a combination of AR model and MA model). Time series travel time prediction models establish the simulation of the travel time trend for a given period on the basis of a known database concerning the variables. Kalman Filter method is a linear quadratic estimation algorithm, which is one of the best prediction methods with high precision and flexibility. However, as a linear estimation model, when the prediction interval becomes less than 5 minutes, whether the model can maintain a strong performance is worth further study. Regression models measure various factors affecting travel time. The advantages of regression models are the capability to reveal the importance of each factor influencing the prediction. However, the regression models are limited in applicability because the factors are often correlated with each other. Particularly, neural network-based approaches are widely applied to predict travel time on the freeway because of the prediction accuracy. While there are several flaws regarding neural network-based methods, such as the lack of generalizability and
transferability. Mehmet and Geroliminis (2013) combine the physic model (e.g., shockwave analysis and bottleneck identification) and statistic method and makes use of both historical and real-time traffic information for travel time prediction. Zhang (2013) evaluated the effects of different input settings on travel time prediction accuracy using artificial neural networks. Their results reveal that volume, occupancy and speed may be used as sole input, but combing all three variables together yields better results. A time-delayed state-space neural network (TDSSNN) was proposed for state-space information input. Zhou et al. (2014) developed a diurnal space-time method for freeway travel time prediction to account for the spatial and temporal correlation and diurnal pattern of travel times. The 5-min average travel time was modeled with two distributions that can provide the distribution of predicted travel times and confidence intervals. Zhang et al. (2015) applied generalized autoregressive conditional heteroskedasticity (ARCH) models to capture the uncertainty. In order to account for trend and seasonality, some variants were made to decompose the data into seasonal, trend, and noise components. Duan et al. (2016) applied LSTM neural network that reserves the historical sequence information in the model structure. The LSTM model was applied on 66 series prediction LSTM neural networks. The evaluation part includes MAE, RMSE, MRE results on 1-step, 2-step, three steps, and four steps ahead. Zhao et al. (2018) applied tensor completion, and K-nearest means method to address the sparseness of Remote Transportation Microwave Sensor (RTMS) technology. Their input includes speed, volume, time of day, and congestion level, and achieve improved data quality and prediction precision of travel time. Li et al. (2018) developed a Diffusion Convolutional Recurrent Neural Network (DCRNN), a deep learning framework for traffic forecasting considering both spatial and temporal dependency. The DCRNN model is designed for road networks using random walks for spatial-temporal modeling, an encoder-decoder architecture for temporal modeling. Kwak and Geroliminis (2018) designed dynamic linear models (DLMs) to approximate the non-linear traffic states. The DLMs assume their model parameters are constantly changing over time, which is used to describe Spatio-temporal characteristics of temporal traffic data. Given the success of the Attention mechanism in many fields, Ran et al. (2019) integrated the attention mechanism with the LSTM model to construct
the depth of LSTM and model the long-range dependence. Chiabaut and Faitout (2021) developed a congestion map-based method that combines historical data with real-time data to predict travel time. The historical data were classified with Gaussian Mixture Model and K-means algorithm to estimate congestion propagation using a consensual day. Abdi and Amrit (2021) surveyed 117 papers from 2010 to 2021 on travel time and arrival travel time prediction methods. The survey paper lists several performance measures, model factors, datasets, explains the strengths and limitations.

HIERARCHICAL LSTM MODEL

Long-Short-Term-Memory Cell

In this section, we briefly describe the building LSTM unit and its key components and variants (Greff et al., 2016). LSTM is modified from the vanilla RNN (Recurrent Neural Network) model to enhance the capability of long-term temporal dependence for sequential feature extraction. LSTM has shown great performance on many language tasks or time-varying data modeling. The classic LSTM cell has led to several variants by adding new modifications, such as ConvLSTM (Shi et al., 2015), Grid LSTM (Kalchbrenner et al., 2015), and Eidetic LSTM (Wang et al., 2019). A widely used variation is the Peephole connections (Gers et al., 2000), allowing each gate within the LSTM unit to use information from cell state. Three main gates were collectively used for progressively updating the output: Input Gate, Output Gate, and Forget Gate. The key feature of LSTM is the Cell State, which works as the memory pipe to transmit the long-term memory stored in the previous state to the current state. The input and forget gates are used as knobs to determine which information needs to be deleted or added to the cell state. Equation (5) describes how the current cell state adds or forgets information with the forget gate and the input gates. The output gate takes the inputs, newly updated long-term memory, and previous short-term memory to compute a new hidden state/short-term memory. A typical LSTM unit model (Zaremba and Sutskever, 2015) is iterated as follows:
\[ i_t = \sigma(W_{ix}x_t + W_{ih}h_{t-1} + b_i) \]  \hspace{1cm} (2)
\[ f_t = \sigma(W_{fx}x_t + W_{fh}h_{t-1} + b_f) \]  \hspace{1cm} (3)
\[ o_t = \sigma(W_{ox}x_t + W_{oh}h_{t-1} + b_o) \]  \hspace{1cm} (4)
\[ c_t = f_t \odot c_{t-1} + i_t \odot \hat{c}_t \]  \hspace{1cm} (6)
\[ h_t = o_t \odot \sigma(c_t) \]  \hspace{1cm} (7)

Where \( f_t \) is forget gate at timestamp \( t \), \( c_t \) is the cell state at timestamp \( t \), and \( o_t \) is the output gate at timestamp \( t \). \( \sigma \) represents a sigmoid operation and \( \varnothing \) represents \( \tanh \) activation function. \( \odot \) is the Hadamard product. \( W \) is the weight matrix that conducts affine transformation on the input \( x_t \) and hidden state \( h_t \). Matrices are depicted with capital letters while vectors with non-capital bold letters.

**Fig 1 LSTM Unit**

**Multi-Layer LSTM**

Existing LSTM-based travel time prediction models are created using the stacked architecture (Cui et al., 2020). As shown in Fig 2, in the stacked LSTM, the upper-level LSTM unit indistinguishably takes in the input from the lower layer of LSTM. After feature extraction with multi-layer LSTM, the fully connected layer is used to calculate the score for the final output.
Before passing the features from previous LSTM layers to the fully connected layer, the self-attention module is often used that can further address the temporal dependence for time-varying data modeling. The attention module computational graph is shown in Fig 3. The numbers in the parenthesis are parameter values used in our designed models.

Hierarchical Module

We introduce the newly designed hierarchical LSTM architecture for travel time prediction. The hierarchical LSTMs have a pooling layer that takes selected features from
the hidden states of LSTM. With this mechanism, the sequential inputs are grouped into different timesteps so that the upper layer can learn the information at different time steps.

The proposed hierarchical LSTMs are shown in Fig 4 and Fig 5, including between layer Hierarchical LSTMs and Output Layer Hierarchical LSTMs. For the between-layer hierarchical LSTM model, the two-level LSTMs are treated differently. The bottom layer processes the entire time sequence, while the top layer only takes the lower-level hidden states from selected time steps and treats the selected hidden states as a new time sequence input.

Fig 4 Between Layer Hidden State Hierarchical LSTM (hiLSTM)

For the output layer Hierarchical LSTM with attention (hiLSTMat), the two-level LSTMs are the same as stacked LSTMs. The hierarchical information extraction happens at the output layer, where the hidden features of the stacked LSTMs were extracted from different time steps. The hierarchically pooled hidden states were forwarded to a self-attention module for dimension reduction. Then the attention layer output was subsequently sent to a fully connected layer to compute results.
TIME SERIES ANALYSIS

In this section, we performed EDA (Explorable Data Analysis) to visualize the trend of travel time data and demonstrate how the work from home (WFH) policy could affect travel time during the COVID-19 pandemic. We can see from the monthly average and daily plots (Fig 6), the travel time in March 2020 has a rapid decline and then gradually gets back for the rest of the year, showing the traffic was impacted by the quarantine policy.

Fig 6 Daily and Monthly Average Travel Time Data
The main feature of time series is autocorrelation and stationarity. Autocorrelation is the correlation for the data with itself at previous timestamps. Time series data are stationary if they do not have trends or seasonal effects, which are the recurring patterns of the data mean and variance for repeated time periods. We conducted the stationery and autocorrelation analysis to reveal the underlying patterns of travel time characteristics.

A very high autocorrelation in travel time data has been identified after calculating autocorrelation and partial autocorrelation because traffic conditions 5 minutes ago will most likely affect the current travel time. As time increases, the correlation declines more and more (see Fig 7).

Stationary is an underlying assumption of many statistical tests. The non-stationary data are often transformed to become stationary. The Augmented Dickey-Fuller (ADF) test was applied to examine if the travel time is stationary. The null hypothesis of ADF is the time series is not stationary. The test result consists of the test statistic and some critical values for different confidence levels. If the test statistic is less than the critical value, the data is considered stationary. The lower the statistic value, the more confidence we can have to reject the null hypothesis in the ADF test.

Fig 7 Travel Time Data Autocorrelation Analysis
In Fig 8, we show that the non-stationary travel time is transformed into stationary data after log function and subtracting the moving average. In the first graph, we can tell from both the overall trend and rolling average that there is a visible gap. Also, from the Dickey-fuller Test, we can see that our test statistic is -0.666 and is higher than the critical value thresholds for any level of confidence. Therefore, we cannot reject the null hypothesis and admit that there exist regime changes in the travel time dataset. Then we try to remove overall trends and seasonality through log series analysis and run it through the ADF test. There is less of a trend in terms of the slope of the average line; however, the test statistic -0.716 is still higher than the suggested critical value. Finally, we compute a moving average and subtract that off from the log value. ADF test statistic of -9.788 falls well below the critical value for all three confidence levels. We can say that we have dampened the overall trend, and now we have a stationary time series distribution.

![Fig 8 Travel Time Data Transformation and Stationary](image-url)
### EXPERIMENT

**Comparable Models**

We implemented three categories of models, including regression models, statistical models, and deep learning models.

For regression models, ElasticNet and Random Forest models were implemented with proper feature selection and transformation. The input features consist of previous travel time records and hour, weekday, and month. The date-time information is one-hot encoded. Ninety-seven different models for each corridor were trained to predict travel time at 15-minute, 30-minute, and 45-minute horizons.

For statistical models, ARIMA and SARIMA Models were used. A stepwise approach is used to search multiple combinations of parameters (number of lag observations, degree of differencing, size of the moving average window) and choose the best model that has the lowest Akaike's Information Criteria (AIC) score. We created 97 different models for each corridor to predict short-term travel time at 15-minute, 30-minute, and 45-minute horizons.

For Recurrent Neural Network (RNN) models, we implemented the stacked LSTM model followed by fully connected layers, between-layer hiLSTM, and output layer hiLSTM. The input data are encoded in a spatial-temporal format. At each time step, travel time data from all corridors are fed into the deep learning model to capture the spatial-temporal influence. Given the N corridors in the study area and 5-minute resolution data, the previous 2-hour travel time records of corridor $j$ are denoted as \( \{ t_{jT-23}, t_{jT-22}, \ldots, t_{jT} \} \) \( j \in [1,N] \). The deep learning model output is the travel time at future time stamp $T + \delta t$ for all corridors \( \{ t_{T+\delta t}^{1}, t_{T+\delta t}^{2}, \ldots, t_{T+\delta t}^{N} \} \). The training, validation and testing dataset were random generated with sample sizes of 12000 (60%), 4000 (20%) and 4000 (20%).
Evaluation Metrics

Several performance metrics are used to evaluate the model performances. Mean absolute error (MAE) is used to measure model accuracy. Root mean square error (RMSE) is sensitive to model stability. Mean Absolute Percentage Error (MAPE) is frequently used as travel time prediction model performance.

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (T_y(t) - T(t))^2} \]  

(8)

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |T_y(t) - T(t)| \]  

(9)

\[ MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|T_y(t) - T(t)|}{T(t)} \]  

(10)

Table 2 Model Prediction Evaluations for Different Horizons

| Prediction Horizon | 15 min | 30 min | 45 min |
|--------------------|--------|--------|--------|
|                    | MAE    | RMSE   | MAPE   |
| ElasticNet         | 0.29   | 0.52   | 2.32%  |
|                    | 0.38   | 0.72   | 2.96%  |
|                    | 0.44   | 0.84   | 3.43%  |
| Random Forest      | 0.27   | 0.58   | 1.94%  |
|                    | 0.34   | 0.72   | 2.42%  |
|                    | 0.36   | 0.77   | 2.59%  |
| ARIMA              | 0.23   | 0.25   | 1.59%  |
|                    | 0.16   | 0.18   | 1.31%  |
|                    | 0.24   | 0.27   | 1.63%  |
| SARMAX             | 0.24   | 0.30   | 1.22%  |
|                    | 0.18   | 0.21   | 1.35%  |
|                    | 0.40   | 0.48   | 2.92%  |
| Stacked LSTM       | 0.13   | 0.21   | 1.28%  |
|                    | 0.13   | 0.22   | 1.31%  |
|                    | 0.14   | 0.23   | 1.32%  |
| hiLSTM             | 0.65   | 1.04   | 5.53%  |
|                    | 0.63   | 1.05   | 5.40%  |
|                    | 0.61   | 1.02   | 5.19%  |
| hiLSTMat           | 0.06   | 0.12   | 0.65%  |
|                    | 0.08   | 0.14   | 0.81%  |
|                    | 0.08   | 0.14   | 0.83%  |
| Average Error Rate | 0.266  | 0.431  | 2.08%  |
|                    | 0.272  | 0.462  | 2.22%  |
|                    | 0.325  | 0.536  | 2.56%  |

As can be seen from the Table 2 results, on average, the developed models were shown to have good predictive capabilities. The mean absoloution errors and root mean square errors are less than 0.5 minutes. The mean absolute percentage errors are around 2%. Good performance attributes to the proper feature transformation and model selection process. Overall, the neural network group has the lowest error rate. The statistic model group has better prediction results than the regression model group.
However, the hiLSTM did not show significant improvements because the between-layer hierarchical pooling lessened the connectivity of different levels of LSTM units, which undermined the model's capacity. Among all reference and designed models, the hiLSTMat model produces the best results on all-time horizons and metrics. The result indicates that adding multiscale information and attention module to refine the hidden states of LSTMs could enhance the model performance. Readers can find the codes and training records, and testing results from our public repository for the purpose of reproducible research.

CONCLUSION

From the above experiments and discussion, the designed hiLSTMat model stands out among others due to the hierarchical information integration to capture different time and spatial influences. Another important factor regarding big data processing is the capability of the framework to handle complex and large datasets. With the right framework, constructing useful neural networks can make life easier, and the only worry is about getting the right data.

In this research, we use Apache Spark for data loading and processing and build machine learning models to compare to the traditional data engineering tool. We conducted a speed testing by running an $O(n \log n)$ time complexity operation with 6.5 million travel time data records on the same Google cloud computing platform. The Apache Spark returned the results in only 120 seconds. On the contrary, the widely used data science library Pandas takes more than 10 hours to perform the same operation. The efficiency of big data tools is very significant.

For the deep learning models, we also compare MXNet with two popular deep learning frameworks, Tensorflow and Pytorch, by training the same stacked LSTM model. Tensorflow powers a lot of applications in big tech companies and has strong community support. Pytorch is preferred by academic researchers for quickly iterating through different ideas due to its easy-to-understand API. MXNet supports a wide range of languages like R, Scala, JavaScript, C++, and Python, which is particularly designed for efficiency and scalability purposes. In our experiments, the MXNet has the fastest
training speed to finish 1000 epochs after 891.01 seconds, which is approximately 25% faster than Pytorch and 50% faster than Tensorflow. As a deep learning framework optimized for big data applications, the MXNet shows a different loss function over epochs compared to Tensorflow and Pytorch. The optimal time-to-solution (TTS) using MXNet can accelerate model deployment so that transportation data scientists and managers can focus on gathering insights and building solutions.

This research set out to explore two aspects of travel time prediction issues:

1. From the model design perspective, this paper tried to add hierarchical feature pooling to the stacked LSTMs models and shows superior prediction accuracy of using hierarchical pooling on output-layer hidden states. The network travel time data and codes of all mentioned models are made freely accessible for academic purposes.
2. Because not all framework is designed for big data machine learning problems, understanding the speed of data processing and model convergence is critical for any organization to choose the right AI/ML framework. We highlighted the impact of different deep learning frameworks and described the efficiency gain of using the big data platform Apache Spark and Apache MXNet.

Hierarchical LSTM has shown excellent results for video summarization and image captioning (Chung and Bengio, 2016; Lin, Zhong, and Fares, 2022), which capture semantic information and long-range dependencies. For future research, the between-layer hiLSTM model needs to be enhanced with a more flexible design to utilize a context layer with hidden states that can translate the information distilled LSTM into structured representations.

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REFERENCES:

1. Van Lint JW. Reliable real-time framework for short-term freeway travel time prediction. Journal of transportation engineering. 2006 Dec;132(12):921-32.

2. Skabardonis, A., Geroliminis, N.: Real-time estimation of travel times along signalized arterials. Transportation & Traffic Theory (2005)

3. Wan, N., Gomes, G., Vahidi, A., Horowitz, R.: Prediction on travel-time distribution for freeways using online expectation maximization algorithm. In: Transportation Research Board 93rd Annual Meeting (2014)

4. Seybold, C.: Calibration of fundamental diagrams for travel time predictions based on the cell transmission model. VS Verlag für Sozialwissenschaften (2015)

5. Zhang, Y., Haghani, A.: A gradient boosting method to improve travel time prediction. Transp. Res. Part C 58, 308–324 (2015)

6. Zhang, X. and Rice, J. (2003). Short-term travel time prediction. Transportation Research Part C: Emerging Technologies, 11(3-4), pp.187-210.

7. Williams BM, Hoel LA. Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results. Journal of transportation engineering. 2003 Nov;129(6):664-72.

8. Smith BL, Williams BM, Oswald RK. Comparison of parametric and nonparametric models for traffic flow forecasting. Transportation Research Part C: Emerging Technologies. 2002 Aug 1;10(4):303-21.

9. M. Castro-Neto, Y.-S. Jeong, M.-K. Jeong, and L. D. Han"Online-SVR for short-term traffic flow prediction under typical and atypical traffic condition" Expert Syst. Appl., vol. 36, no. 3, pp. 6164–6173, Apr. 2009.

10. P. Gao, J. Hu, H. Zhou, and Y. Zhang"Travel time prediction with immune genetic algorithm and support vector regressio" in Proc. 12th World Congr. Intell. Control Autom. (WCICA), Jun. 2016, pp. 987–992.

11. Liu, X., Chien, S.I., Chen, M.: An adaptive model for highway travel time prediction. J. Adv. Transp. 48, 642–654 (2015)

12. Van Lint JW. Online learning solutions for freeway travel time prediction. IEEE Transactions on Intelligent Transportation Systems. 2008 Feb 26;9(1):38-47.
13. Jiwon Myung, Dong-Kyu Kim, Seung-Young Kho, and Chang-Ho Park, "Travel Time Prediction 46 Using k Nearest Neighbor Method with Combined Data from Vehicle Detector System and Automatic Toll Collection System," Transportation Research Record: Journal of the Transportation 48 Research Board, vol. 2256, pp. 51-59, 2011

14. Hou Y, Edara P. Network scale travel time prediction using deep learning. Transportation Research Record. 2018 Dec;2672(45):115-23.

15. Zhao J, Gao Y, Tang J, Zhu L, Ma J. Highway travel time prediction using sparse tensor completion tactics and-nearest neighbor pattern matching method. Journal of Advanced Transportation. 2018 Mar 14;2018.

16. Van Lint JW, Hoogendoorn SP, van Zuylen HJ. Accurate freeway travel time prediction with state-space neural networks under missing data. Transportation Research Part C: Emerging Technologies. 2005 Oct 1;13(5-6):347-69.

17. Liu Y, Wang Y, Yang X, Zhang L. Short-term travel time prediction by deep learning: A comparison of different LSTM-DNN models. In2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC) 2017 Oct 16 (pp. 1-8). IEEE.

18. Wu, Y., Tan, H., Qin, L., Ran, B., Jiang, Z.: A hybrid deep learning based traffic flow prediction method and its understanding. Transp. Res. Part C Emerg. Technol. 90, 166–180 (2018)

19. Cheng YC, Li ST. Fuzzy time series forecasting with a probabilistic smoothing hidden Markov model. IEEE Transactions on Fuzzy Systems. 2011 Oct 5;20(2):291-304.

20. Joshua W Robinson, Alexander J Hartemink, and Zoubin Ghahramani. 2010. Learning Non-Stationary Dynamic Bayesian Networks. Journal of Machine Learning Research 11, 12 (2010).

21. Emmanuel de Bézenac, Syama Sundar Rangapuram, Konstantinos Benidis, Michael Bohlke-Schneider, Richard Kurle, Lorenzo Stella, Hilaf Hasson, Patrick Gallinari, and Tim Januschowski. 2020. Normalizing Kalman Filters for Multivariate Time Series Analysis. NeurIPS 33 (2020)

22. Williams BM, Hoel LA. Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results. Journal of transportation engineering. 2003 Nov;129(6):664-72.
23. Bandara K., Bergmeir C., Smyl S. Forecasting across time series databases using recurrent neural networks on groups of similar series: A clustering approach. Expert Systems with Applications, 140 (2020), Article 112896
24. Chung J, Gulcehre C, Cho K, Bengio Y. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555. 2014 Dec 11
25. S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural computation, vol. 9, no. 8, pp.1735–1780, 1997.
26. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, Kaiser Ł, Polosukhin I. Attention is all you need. InAdvances in neural information processing systems 2017 (pp. 5998-6008).
27. Luong MT, Pham H, Manning CD. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025. 2015 Aug 17.
28. Abdelraouf A, Abdel-Aty M, Yuan J. Utilizing Attention-Based Multi-Encoder-Decoder Neural Networks for Freeway Traffic Speed Prediction. IEEE Transactions on Intelligent Transportation Systems. 2021 Sep 10.
29. J.-H. Jacobsen, E. Oyallon, S. Mallat, and A. W. Smeulders, "Multiscale hierarchical convolutional networks," arXiv preprint arXiv:1703.04140, 2017.
30. Wehmeyer C, Noé F. Time-lagged autoencoders: Deep learning of slow collective variables for molecular kinetics. The Journal of chemical physics. 2018 Jun 28;148(24):241703.
31. Liu Y, Ponce C, Brunton SL, Kutz JN. Multiresolution convolutional autoencoders. arXiv preprint arXiv:2004.04946. 2020 Apr 10.
32. Shi-Jie Li, Yazan AbuFarha, Yun Liu, Ming-Ming Cheng, and Juergen Gall. Ms-tcn++: Multi-stage temporal convolutional network for action segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2020.
33. Ji Lin, Chuang Gan, and Song Han. Tsm: Temporal shift module for efficient video understanding. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 7083–7093, 2019.
34. Yildirimoglu M, Geroliminis N. Experienced travel time prediction for congested freeways. Transportation Research Part B: Methodological. 2013 Jul 1;53:45-63.
35. Zeng X, Zhang Y. Development of recurrent neural network considering temporal-spatial input dynamics for freeway travel time modeling. Computer-Aided Civil and Infrastructure Engineering. 2013 May;28(5):359-71.

36. Zou Y, Zhu X, Zhang Y, Zeng X. A space–time diurnal method for short-term freeway travel time prediction. Transportation Research Part C: Emerging Technologies. 2014 Jun 1;43:33-49.

37. Li Y, Yu R, Shahabi C, Liu Y. Diffusion convolutional recurrent neural network: Data-driven traffic forecasting. arXiv preprint arXiv:1707.01926. 2017 Jul 6.

38. Kwak S, Geroliminis N. Travel time prediction for congested freeways with a dynamic linear model. IEEE Transactions on Intelligent Transportation Systems. 2020 Jul 22.

39. Ran X, Shan Z, Fang Y, Lin C. An LSTM-based method with attention mechanism for travel time prediction. Sensors. 2019 Jan;19(4):861.

40. Chiabaut N, Faitout R. Traffic congestion and travel time prediction based on historical congestion maps and identification of consensual days. Transportation Research Part C: Emerging Technologies. 2021 Mar 1;124:102920.

41. Greff K, Srivastava RK, Koutník J, Steunebrink BR, Schmidhuber J. LSTM: A search space odyssey. IEEE transactions on neural networks and learning systems. 2016 Jul 8;28(10):2222-32.

42. SHI Xingjian, Zhourong Chen, Hao Wang, Dit-Yan Yeung, Wai-Kin Wong, and Wang-chun Woo. Convolutional lstm network: A machine learning approach for precipitation nowcasting. In Proceedings of the Advances in neural information processing systems, pages 802–810, 2015.

43. Nal Kalchbrenner, Ivo Danihelka, and Alex Graves. Grid long short-term memory. arXiv preprint arXiv:1507.01526, 2015.

44. Yunbo Wang, Lu Jiang, Ming-Hsuan Yang, Li-Jia Li, Mingsheng Long, and Li Fei-Fei. Eidetic 3d lstm: A model for video prediction and beyond. 2019.

45. Gers FA, Schmidhuber J. Recurrent nets that time and count. InProceedings of the IEEE-INNS-ENNS International Joint Conference on Neural Networks. IJCNN 2000. Neural Computing: New Challenges and Perspectives for the New Millennium 2000 Jul 27 (Vol. 3, pp. 189-194). IEEE.
46. W. Zaremba and I. Sutskever. Learning to execute. In ICLR, 2015.

47. Cui Z, Ke R, Pu Z, Wang Y. Stacked bidirectional and unidirectional LSTM recurrent neural network for forecasting network-wide traffic state with missing values. Transportation Research Part C: Emerging Technologies. 2020 Sep 1;118:102674.

48. Chung J, Ahn S, Bengio Y. Hierarchical multiscale recurrent neural networks. arXiv preprint arXiv:1609.01704. 2016 Sep 6.

49. Lin J, Zhong SH, Fares A. Deep hierarchical LSTM networks with attention for video summarization. Computers & Electrical Engineering. 2022 Jan 1;97:107618.