Bus Arrival Time Prediction with LSTM Neural Network

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Task definition

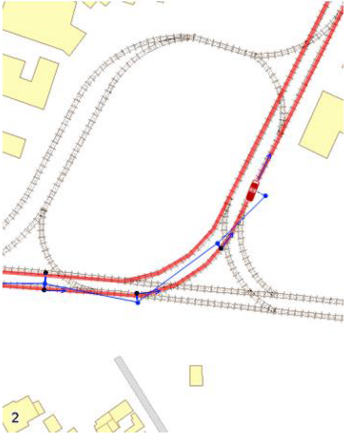
- Public transport arrival time prediction to stops
- Take into account different factors that characterize the traffic state
- Develop a distributed prediction model

Task

- Real-time processing
- High accuracy

Initial data. Preprocessing

- GPS coordinates are obtained every 30 seconds
- Coordinates are fitted using information about the road network geometry and transport routes
- Travel times for each road link are calculated



Problem formulation

- S is the set of stops;
- R is the set of routes;
- N is the maximum number of route links;
- t_i^{dep} the departure time from stop $i \in S$;
- t_j^{arr} is the arrival time at stop $j \in S$;
- T_{ij}^{travel} the travel time between stops i and j.

$$t_j^{arr} = t_i^{dep} + T_{ij}^{travel}$$

Feature vector: base factors

To estimate the travel time T_{ij}^{travel} we used the following factors:

- day, $time$
- $v_{i-1,i}$ - travel speed on the previous route link
- h^r - time headway to the preceding vehicle with the same route
- $T_{ij}^{m,r}$ travel time of the preceding vehicle m with the same route r
- $\tilde{T}_{ij}^{r}$ - weighted travel time of preceding vehicles with the same route:

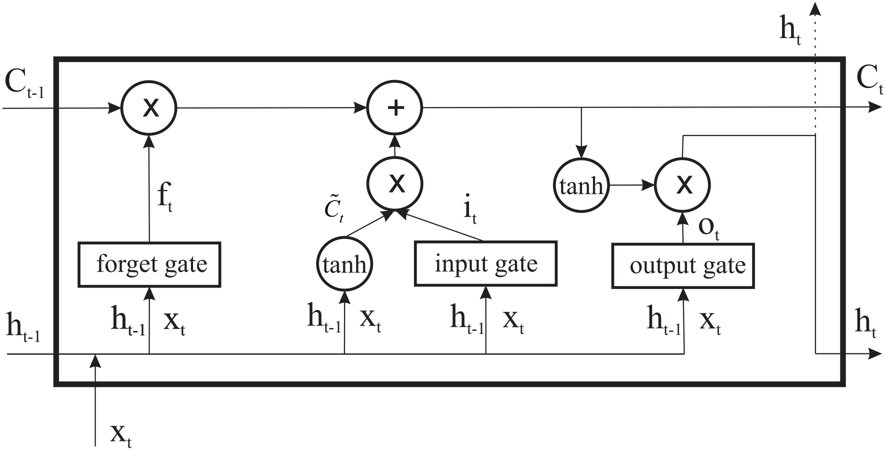
$$\tilde{T}_{ij}^{r} = \frac{\sum_{k \in N_r} \omega\left(t - t_i^{dep,k}\right) T_{ij}^{travel,k}}{\sum_{k \in N_r} \omega\left(t - t_i^{dep,k}\right)}$$

Feature vector

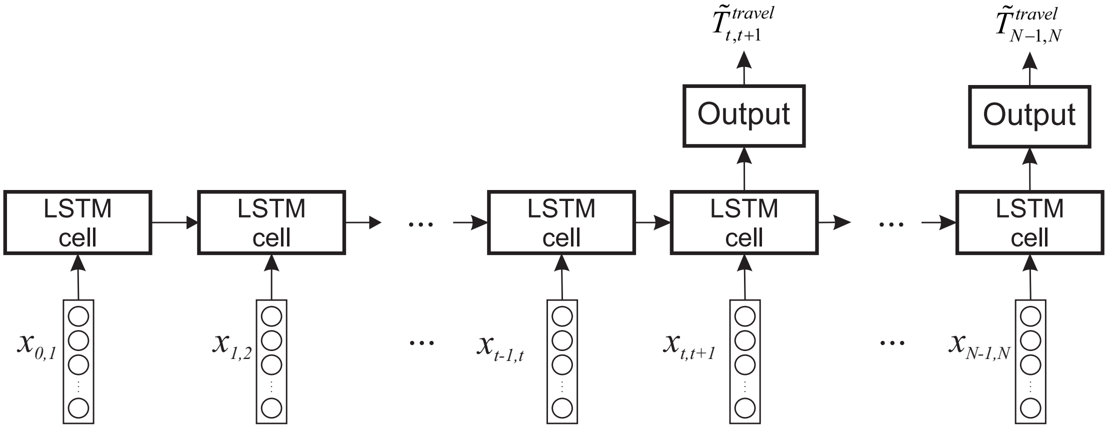
- h^{any} - time headway to the preceding vehicle with any route
- $T_{ij}^{m,any}$ - travel time of the preceding vehicle with any route
- $\tilde{T}_{ij}^{any}$ - weighted travel time of preceding vehicles with any route
- $T_{ij}^{hist}(t)$ - historical average travel time
- $T_{ij}^{flow}(t)$ - historical average travel time by traffic flow data
- c_{ij} - number of vehicles on the targeted route link

$$X_{i,j} = \left(day, time, v_{i-1,i}, h^r, T_{ij}^{m,r}, \tilde{T}_{ij}^r, h^{any}, T_{ij}^{m,any}, \tilde{T}_{ij}^{any}, T_{ij}^{hist}, T^{flow}, c_{ij}\right)$$

Long short-term memory (LSTM) cell

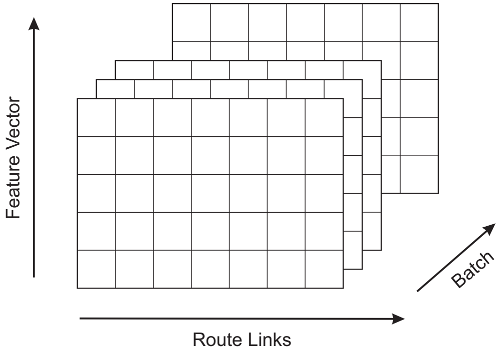


LSTM network

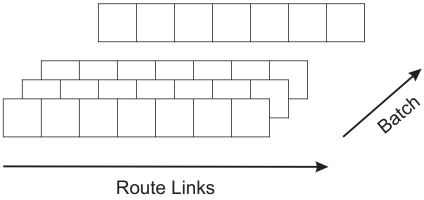


Long short-term memory (LSTM) neural network

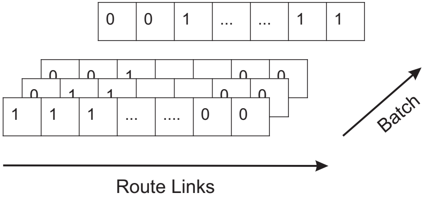
Input data



Output data



Mask



Model analysis

Comparison:

- Proposed / Base LSTM models
- ANN, 1 hidden layer
- Linear Regression

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |V_t - \hat{V}_t|,$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \frac{|V_t - \hat{V}_t|}{V_t} \times 100\%$$

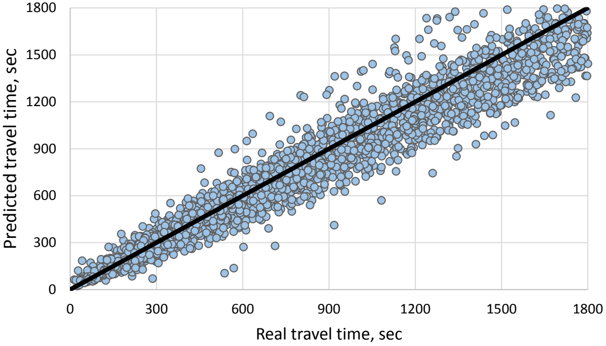
Data set:

- Five bus routes
- Average route length is 16 km
- Travel time observations in 30 days

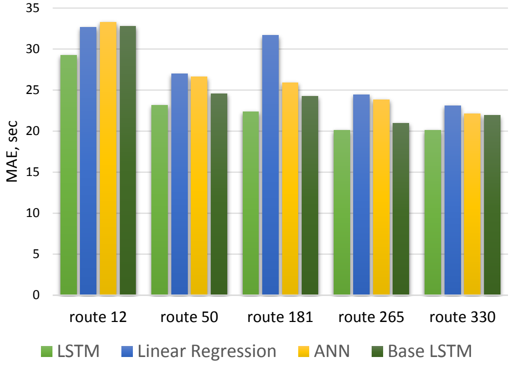
Model analysis. MAE / MAPE

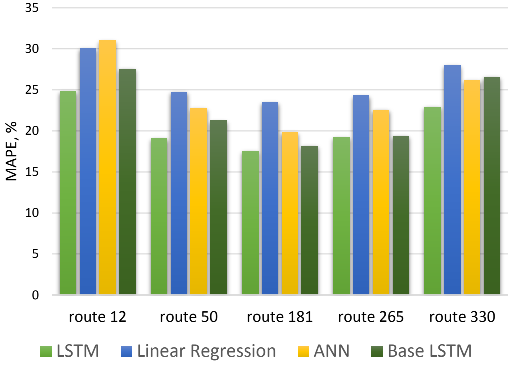
Table: Algorithms Comparison

	MAE	MAPE
LSTM	**22.12**	**19.78**
Base LSTM	23.64	21.24
ANN	25.54	23.25
Regression	26.89	25.19

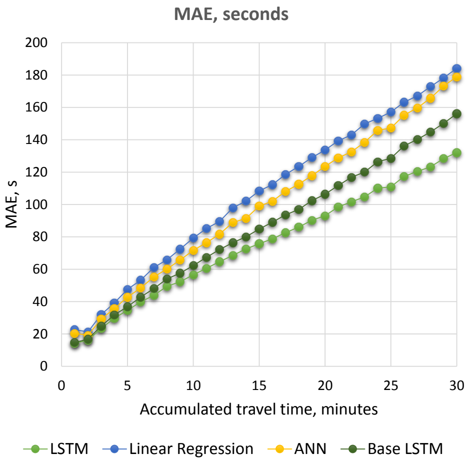


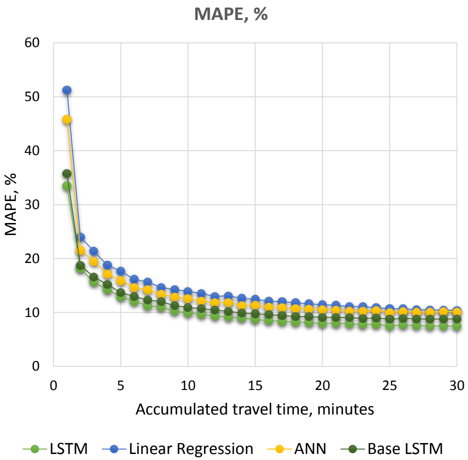
Model analysis. MAE / MAPE for routes





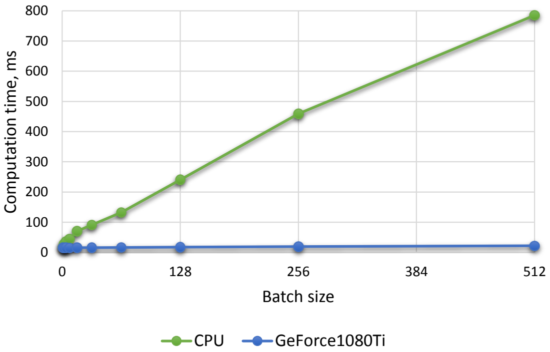
Model analysis. MAE / MAPE

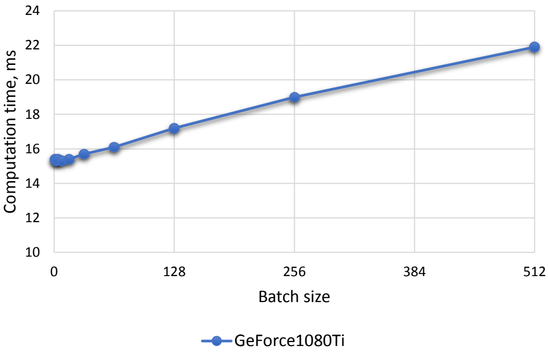




Model analysis. Execution time

Intel Core i5-3740 3.20 GHz, 8 GB RAM / Nvidia GeForce GTX 1080 Ti





Conclusion

The proposed LSTM based arrival time prediction model has the following advantages:

- Combines different factors describing the traffic situation.
- It has high prediction accuracy.
- It has a low computation time.

Thank you!

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