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METHOD FOR AGENT-ORIENTED TRAFFIC PREDICTION UNDER DATA AND RESOURCE CONSTRAINTS

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ABSTRACT

Context. Problem of traffic prediction in a city is closely connected to the tasks of transportations in a city as well as air pollution detection in a city. Modern prediction models have redundant complexity when used for separate stations, require large number of measuring stations, long measurement period when predictions are made hourly. Therefore, there is a lack of method to overcome these constraints. The object of the study is a city traffic.

Objective. The objective of the study is to develop a method for traffic prediction, providing models for traffic quantification at measuring stations in the future under data and resource constraints.

Method. The method for agent-oriented traffic prediction under data and resource constraints was proposed in the paper. This method uses biLSTM models with input features, including traffic data obtained from agent, representing target station, and other agents, representing informative city stations. These agents are selected by ensembles of decision trees using Random Forest method. Input time period length is proposed to set using autocorrelation data.

Results. Experimental investigation was conducted on traffic data taken in Madrid from 59 measuring stations. Models created by the proposed method had higher prediction accuracy with lower values of MSE, MAE, RMSE and higher informativeness compared to base LSTM models.

Conclusions. Obtained models as study results have optimal number of input features compared to the known models, do not require complete system of city stations for all roads. It enables to apply these models under city traffic data and resource constraints. The proposed solutions provide high informativeness of obtained models with practically applicable accuracy level.

KEYWORDS: traffic, prediction, times series, LSTM, bidirectional LSTM.

ABBREVIATIONS

biLSTM is a bidirectional LSTM;
LSTM is a Long Short-Term Memory;
MAE is a Mean Absolute Error;
MSE is a Mean Squared Error;
RMSE is a Root Mean Square Error.

NOMENCLATURE

$auto_{\min}$ is a threshold value for autocorrelation;

B is a set of stations used for traffic quantification in a city or stations with data available for model creation;

B^S is a subset of stations selected from a set B based on the measurement of its impact on traffic at station A;

Cr is a limit number of stations possible to select to a subset B^S;

E is a set of factors, having impact on traffic values at station A during each of $(t + 1)$, …, $(t + h)$ hours;

E^K is a set of determined factors, having impact on traffic values at station A;

E^U is a set of undetermined factors, having impact on traffic values at station A;

f is a functional dependency to be determined by creation of traffic prediction model for station A;

H^F is a number of next hours from the current moment, which defines prediction horizon;

H^P is a number of previous hours from the current moment t, used for prediction;

t is a number of the current hour, i.e. moment in time when prediction is made;

T^{tr} is a length of training period;

tr_A^t is a traffic value at station A during the t-th hour;

v_e^t is a value of factor e from set tr_A^t during the t-th hour;

v_u^t is a value of factor u from subset of undetermined factors E^U during the t-th hour.

INTRODUCTION

Traffic is defined by number of vehicles moving through some location during some period of time [1]. Measuring stations are used to detect traffic and to quantify it at different locations.

Traffic is a structurally important concept, determining corresponding related processes in a modern city. Quality of life is closely connected to how traffic is managed in a city. Related flows should be clearly directed during city planning. Corresponding traffic rules as well as city construction principles should be set. Principles of construction of old cities did not take into account modern transport requirements, therefore transportations by vehicles in such cities are complicated. At the same time every modern city with correct planning restricts vehicle

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movements according to certain principles, so it is not also totally free [2]. However, besides long-term traffic management, monitoring and informing about transport flows are important in short term as well [3].

Modern city traffic has influence on ecology. Cities set special restrictions on cars moving inside an area within city boundaries. These restrictions are gradually expanded. Strategic transition to electric cars is executed, but at the moment the majority of vehicles use fossil fuel, having negative influence on ecology.

Large part of emissions is caused by vehicles. Such air pollutants include nitrogen dioxide, benzol etc. In different cities percentage of influence of vehicles on air pollution varies. But the fact that vehicles are one of the main reasons of air pollution in modern cities is widely known. Besides, traffic is correlated with business activity. Therefore, absent or low traffic corresponds to low business activity and low air pollution at least in terms of concentration of pollutants closely connected to vehicle emissions. As a result, information about quantity of vehicles moving through some location in a city over a period of time helps to understand expected air pollution.

Prediction of traffic in a city may be valuable for every citizen while seeking for optimal path for transportation to the given location. It additionally emphasizes that city traffic has a significant influence on citizens in a city. Information about traffic in the short term allows citizens to plan their personal journeys in terms of its duration and in terms of impact on their health as well. The second factor is explained by causation between traffic and air pollution as well as air pollution and negative health impact even in the short term.

Taking it into account, it is obvious that traffic prediction problem is a significant practical problem. Besides, it is a significant scientific problem as well. A lot of factors have influence on traffic, so it is important to determine prediction models correctly.

The object of the study is a city traffic.

The subject of the study are traffic prediction models based on LSTM.

The objective of the study is to develop a method for traffic prediction, providing models for traffic quantification at measuring stations in the future under data and resource constraints.

1 PROBLEM STATEMENT

Problem of traffic prediction is a problem of traffic quantification at station A during each of H^F hours in the future using data on traffic at station A during previous H^P hours and data on other factors from set E defined by formula (1):

$$tr_A^{t+h} = f(tr_A^t, tr_A^{t-1}, ..., tr_A^{t-H^P-1}, v_e^t, v_e^{t-1}, ..., v_e^{t-H^P} \quad h = \overline{1, H^F}, e \in E. \tag{1}$$

Solving problem (1), H^F values of traffic tr_A^{t+h} at station A should be computed. Each value represents traffic over the ($t + h$)-th hour, determined by time period, starting at $t + h$ hour 0 minutes and ending at $t + h$ hour 59 minutes in the future. These computations should be made using functional dependence f and H^P values of traffic at station A in the past: $tr_A^t, tr_A^{t-1}, ..., tr_A^{t-H^P-1}$. As current moment defines finish of historical period, value of H^P comprises current hour with number t. Traffic at the moment t is quantified and known, so the last value (or called the first one otherwise) of input time period has number $H^P - 1$.

In this paper traffic is considered at hourly intervals. Therefore, every feature of observation should represent data collected over an hour. It includes data collected for all directions. If vehicles are moving in two directions through some location, then corresponding value of traffic is calculated as sum of number of vehicles moving towards a sensor called measuring station and in the opposite direction. If measuring station is located at crossroads, traffic should be computed as sum of all values determined for every direction. It enables to determine activeness of transport flows in general. If a vehicle moved twice or more times through some location in one or several directions over an hour, then it has to be calculated corresponding number of times. Therefore, this problem is connected with calculation of general number of vehicle drives through a location but not with identification of unique vehicles. Different approaches were proposed to organize work of measuring stations [4].

Set of factors E comprises subset of determined factors E^K, which impact was corroborated, and subset of undetermined factors E^U, representing impact of uncertainty. Solving problem (1) by creating traffic prediction model, subset E^U should be decreased at the expense of increasing subset E^K. But it is impossible to take into account all factors, which have influence on output, in the current state of development of world science. Therefore, influence of factors from subset E^U is active. It causes differences between output got by trained model and actual values of traffic for the same station over the same period of time.

2 REVIEW OF THE LITERATURE

Review of the literature was conducted based on the sequence of sources [5–14], taking into account results, represented in reviews of literature [5–6]. Results of the review demonstrate that big part of studies is directed at unification of models based on deep neural networks and models, applicable for taking into account spatial dependencies between measuring stations. This approach enables to create model, capable to process data from all stations simultaneously and to make predictions about future states of these stations. It is considered in the following studies in particular.

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In the paper [7] it was proposed to use combined model based on graph convolutional neural network to extract characteristics of topological structure from traffic data, LSTM to extract characteristics of temporal structure and convolutional neural network to optimize general model. 5, 15 and 30 minutes were investigated as possible length of input time intervals. Model performance was evaluated by MAE, MSE and R^2. The longer input time interval was, the worse results were obtained. Experimental investigation was conducted on data collected in California (USA), using 39000 sensors.

In the paper [8] hybrid graph model was created. Unlike the previous model, it applies dynamic graph besides static one, representing topology of the traffic system as well as enabling to update it according to the current conditions. The proposed model combines graph neural network and convolutional neural network, applying attention mechanism. This solution enables to extract spatio-temporal characteristics. Experimental investigation is conducted on two datasets collected in California (USA). Obtained results were evaluated by MAE, RMSE and mean absolute percentage error as well.

Authors in the paper [9] proposed to use spatio-temporal graph convolutional network. Investigation was conducted for input time period of 60 previous minutes and prediction was executed for 15, 30 or 45 minutes. Results obtained on data collected in Beijing as well as in California demonstrate accuracy decrease for longer prediction periods. Accuracy for prediction period of 15 minutes is more than 1.5 times as much as accuracy for prediction period of 45 minutes.

Besides, there is a number of researches on traffic prediction where other traffic indicators are used. In particular speed prediction is researched in the paper [10]. It's not strictly a problem considered, but similar structures are used for problem solving. The proposed model is based on convolutional neural network, LSTM, attention mechanism and 2 biLSTM. Similar solutions are proposed in the paper [11].

However practical applicability of these models is questionable in some cases. It demands high-performance computing, because resulting models have relatively complex structure, and data access which may be hard to provide. The last obstacle may be caused by absence of necessary historical data as it should have appropriate period which is possibly long. The more complex model structure, the longer period should be. Cities in developing countries may have fragmented traffic data, which do not cover all streets and crossroads or even a subsystem of roads. Therefore, it is hard to create a complete model. As a result, spatial dependencies are broken, because some locations in entire road system are absent. Besides, data may be inaccessible over a long period of time. For example, martial law can prohibit transmitting traffic data partially or completely, so open access services are restricted.

Moreover, prediction of traffic for every location in a city can be unnecessary. Then potential number of input features is far more than number of outputs. At the same time not all input features are necessary, so model complexity is excessive. It means that part of data is noisy and is separated by model structure. So, part of model structure is used not for prediction purposes but for separation of noisy data. On the other hand, when traffic prediction models give inputs for air pollution prediction, it should be taken into account that air pollution measuring stations are located at particular positions and its quantity is limited. Then approach proposed in papers [7]–[11] is inapplicable. In addition, it should be noted that results of conducted researches and other studies which were analysed demonstrate that traffic prediction for more than an hour is an individual problem and needs detailed investigation for improvement of results.

However, there is a number of studies which do not take into account spatial dependencies, being applicable for solving problem (1) under constraints on traffic data in a city. This approach is represented in the papers [12]–[14], and such technologies are applied for different problems, in particular [15–16].

In the paper [12] traffic is predicted based on LSTM models for 15, 30, 45, 60 minutes.

Traffic prediction for a period up to 60 minutes is investigated in the paper [13], using biLSTM models with 1 input feature and simulation data.

In the paper [14] biLSTM prediction is executed for 5 minutes, taking into account precipitation and visibility as additional features.

Therefore, it is necessary to develop results of researches [12–14]. Usage of additional features, principles of feature selection, investigation of input time period should be researched.

3 MATERIALS AND METHODS

Based on the problem statement (1), traffic prediction problem was analysed and general principles of problem solving were set. Time horizon for prediction was set equal to 6 hours in this study. However, the method for traffic prediction presented in this chapter uses principles of hourly data and making predictions for H^F hours ahead. So, it is applicable for other time periods.

Target measuring station A for which prediction is made has to be set as an input parameter for the method. All following stages are executed for this station. It should be presented by corresponding agent when prediction is made by for real-time data. Logic sequence of the proposed stages defines method for traffic prediction presented in Fig. 1.

At the initial stage of the method training dataset has to be created. Training dataset should contain data from all available stations from set B. All observations for each station have to represent each possible date and hour from training period. Every observation is defined by time series containing $H^P + H^F$ sequential hours.

Therefore, it is necessary to determine all hours in period of time defined as training to set training dataset. Training period is defined by time interval for which traffic data is available for all stations included in this data-

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set. Values for some hours may be missed. For that reason, starting from the earliest available date and time (hour) every timestamp should be created with a step of 1 hour until the latest available date and time. Only when it is finished, each created timestamp should be connected with corresponding number of vehicles moved through location defined by each station over this period of time. After all available observations are set, missed values should be filled by linear interpolation.

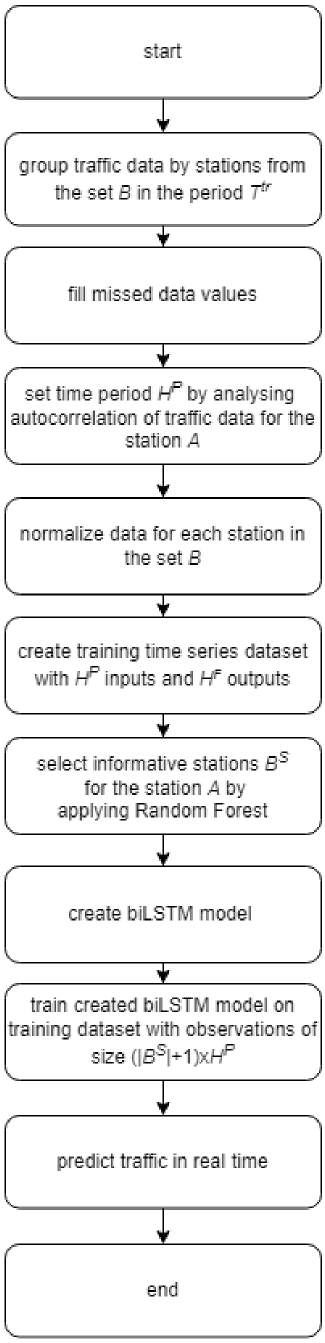

Figure 1 – Sequence of traffic prediction model training stages

Then value of H^P should be set. This parameter is influenced by value of H^F and it impacts on accuracy of predictions made by created models. So, this choice is important. The following procedure was defined to make this choice. Autocorrelation should be computed for values of traffic for station A with appropriate maximum lag. Maximum lag is a maximum possible value of H^P. Value of H^P should be set in such a way that autocorrelation with lag H^P is equal or higher than threshold value $auto_{\min}$. Threshold value $auto_{\min}$ should be set based on data analysis conducted for all available measuring stations. Otherwise it should be chosen to fulfill special requirements for predictions.

Then maximum and minimum values have to be got from training dataset for each station to normalize data. After normalization is finished, time series is created for every observation by appending elements for the next $H^P + H^F - 1$ hours. These elements are created by data shift.

Problem (1) is a problem of time series forecasting. So, values of traffic at a station over previous hours are used as values of input features. But every station is not totally separate. It is dependent on some other stations and it possibly has influence on some other stations. When entire set of stations is considered as input, it complicates model. However, it does not mean that existing dependence should not take into account at all. When optimal number of input features is investigated, dependence between values of traffic at station A, for which prediction is made, and at all other available stations from set B should be considered. As a result of this stage subset $B^S \subseteq B$ should be set. Subset B^S comprises stations selected from set B based on degree of influence of traffic at the selected stations on traffic at station A. This degree should be considered as significant.

Subset of stations B^S has to be created from set of stations B excluding station A at the following stage. It is proposed to use ensembles of decision trees using Random Forest method for this purpose.

Limit (maximum) number of stations Cr has to be set while method is applied. This number determines maximum number of additional features for final model and power of set B^S. Set of power $|B^S|$ has to be got as an output. It has to be not larger than the given limit number of stations Cr.

At the next stage biLSTM model [17–18] has to be created for station A with the next structure:

– input layer which corresponds to the structure described below;

– the first hidden bidirectional layer;

– dropout;

– the second hidden bidirectional layer;

– fully connected layer with H^F neurons for getting output values.

This model should detail dependence defined by the problem statement (1) in a way defined by formula (2):

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$$tr_A^{t+h} = f(tr_A^t, tr_A^{t-1}, ..., tr_A^{t-H^P-1}, tr_b^t, tr_b^{t-1}, ...,$$
$$tr_b^{t-H^P-1}, ..., v_u^t, v_u^{t-1}, ..., v_u^{t-H^P-1}), \quad (2)$$
$$h = \overline{1, H^F}, b \in B^S, B^S \subseteq B, e \in E.$$

So, input data for this model has to be determined by matrix of size $(|B^S|+1) \times H^P$. Rows of matrix contain traffic data from $|B^S|$ stations and from station A, for which model is created.

At the next stage model created at the previous stage has to be trained. Early stopping should be applied for training procedure to prevent overfitting.

When model is applied for real-time predictions, data is collected from agents, representing stations. These steps should be applied every hour. Every agent enables access to data, collected for the last hour. Agent should aggregate data, collected by sensor or any appropriate device located at station. When request is received, agent should send aggregated data to agent requested data. Connections are created between agents representing relevant stations. When data from all relevant stations is received, it should be united with data from target station and necessary historical data. Then prediction should be made using trained model. An observation presented as matrix of size $(|B^S|+1) \times H^P$ has to be used as input data. Every agent represents one station and has trained model for predictions. Corresponding sequence of real-time traffic prediction stages is presented in Fig. 2.

Results of the method include a trained model applicable for traffic prediction as well as number of hours H^P and subset of stations B^S.

Figure 2 – Sequence of real-time traffic prediction stages

4 EXPERIMENTS

Experimental investigation was conducted on dataset created from traffic data taken in Madrid (Spain) from 59 measuring stations and published in open access at Open data portal [19] of Madrid City Council [20]. The data was collected at 60 stations in Madrid. Data from 1.01.2019 until 30.09.2022 was used for investigation. As data analysis revealed absence of data at Calle Arenal station for the given period, it was excluded from the following investigation. Data from 59 stations was used for experimental investigation as a result. Each station provided quantification of traffic in two directions. Therefore, downloaded dataset was processed and aggregated, accumulating values in two directions for obtaining each station's hourly values.

Every file of initial dataset contains traffic data collected over a month. Every row in a file has a structure with the following columns:

– datemark, determining date when data observation was made;

– number of measuring station;

– additional mark (the first part of the day and forward traffic direction, the first part of the day and reverse traffic direction, the second part of the day and forward traffic direction, the second part of the day and reverse traffic direction);

– sequence of columns presenting traffic values for 12 hours separately.

Data was aggregated and saved to the united dataset. The dataset contains data for each station separately as well as a list of timestamps presenting date and time (hour and minutes) when corresponding observation was made. Every observation for every station contains normalized quantity of vehicles moved through location defined by measuring station in forward and reverse directions during time moment defined by corresponding timestamp. Quantity of vehicles moved through location was computed for hours until 12 as a sum of number of vehicles moved through location in forward and reverse directions per corresponding hour of the first part of a day (the first and the second marks were applied). The same procedure was used for hours of the second part of a day (the third and the fourth marks were applied).

80 % of data observations from the final dataset were used to create training dataset, other 20 % were used for test dataset. This separation was executed, taking into account batch size. The value of correspondent parameter BATCH_SIZE was set for training. The value of this parameter was set to 32. Therefore, number of observations in training dataset was coordinated with batch size to be divided without a remainder. If it wasn't true from the beginning, then number of observations in dataset was decreased by adding observations to test dataset. After this procedure was finished, number of observations in training dataset had to become divided by batch size without a remainder.

Creation of prediction models was based on the number of common principles: every model had an input layer, 2 hidden layers with dropout between layers, fully

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connected layer for getting output value. Optimization was done using Adam optimizer. Loss function was determined by MSE. Maximum number of training iterations was set to 500. Early stopping criterion was determined for preventing model overfitting: if 40 iterations in a row didn't improve training results (loss function value didn't decrease), then training had to be stopped.

Final biLSTM models were created with 32 cells in two hidden bidirectional layers. Dropout was set to 0.1. Limit number *Cr* was set to 2 when Random Forest method was applied for selection of relevant stations. That is why maximum number of input features model could have was 3 with corresponding length of input time period.

Training dataset was divided into the part used for training directly (75 % of training dataset or 60 % of the united dataset) and the part used for validation (25 % of training dataset or 20 % of the united dataset).

The following models were investigated:

– LSTM models which use traffic data values for the previous 6 hours collected at target station as an input feature;

– biLSTM models which use traffic data values for the previous 6 hours collected at target station as an input feature;

– biLSTM models which use traffic data values for the previous 6 hours collected at target station and at selected stations considered relevant for target station as input features;

– biLSTM models which use traffic data values for the previous 24 hours collected at target station and at selected stations considered relevant for target station as input features;

– final biLSTM models created by the proposed method which use traffic data values for the optimal number of previous hours collected at target station and at selected stations considered relevant for target station as input features (marked by 3 features, adjusted 24/6 previous hours).

The following indicators were used for evaluation of model performance: MSE, RMSE, MAE, R^2.

Evaluation was executed using output values of each hour predicted by model separately. These values were compared with corresponding values from test dataset to compute values of model performance indicators (MSE, RMSE, MAE). Besides average values of model performance evaluation indicators for each station, average values of MSE were computed for each hour separately. Using computed values of model performance evaluation indicators for each station, minimum, maximum and average values were computed for each indicator.

5 RESULTS

All results were obtained only on test dataset. Observations from training dataset were used only for model training.

Distribution of MSE values is important for interpretation of results. Overall distribution of MSE values for biLSTM models (3 features, 6 hours), containing all 6 hours, is presented in Fig. 3. These models have 3 input features based on data traffic determined for the previous 6 hours. 3 features include target station and 2 additional stations selected as relevant for station of the first feature.

Each histogram defines number of models with certain characteristics created and trained for different stations (it should be represented as number of stations or models for these stations).

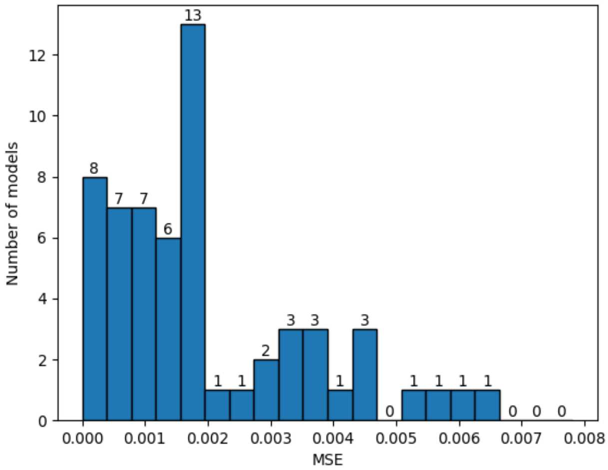

Figure 3 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations

The corresponding distribution of MSE values for models, created by the proposed method (with adjusted time period) for different stations, is demonstrated by histogram in Fig. 4.

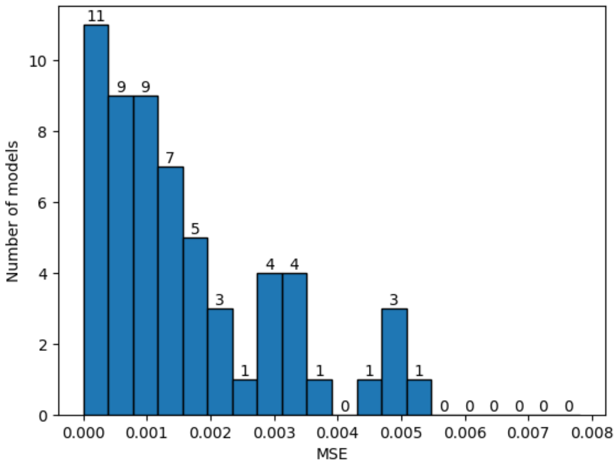

Figure 4 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations

The previous tables and figures contain results concerning all hours for which prediction was made. But there could be different trends in prediction for different step (number of corresponding hour). As prediction horizon was 6 hours, distribution of MSE values for biLSTM models (3 features, 6 hours) is presented for each hour in Fig. 5–10.

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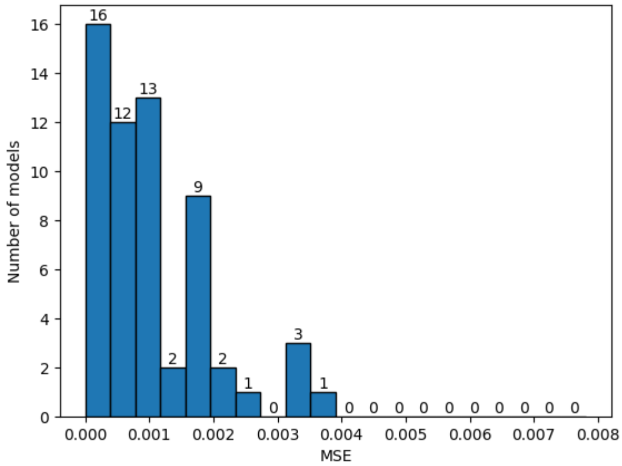

Figure 5 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in an hour

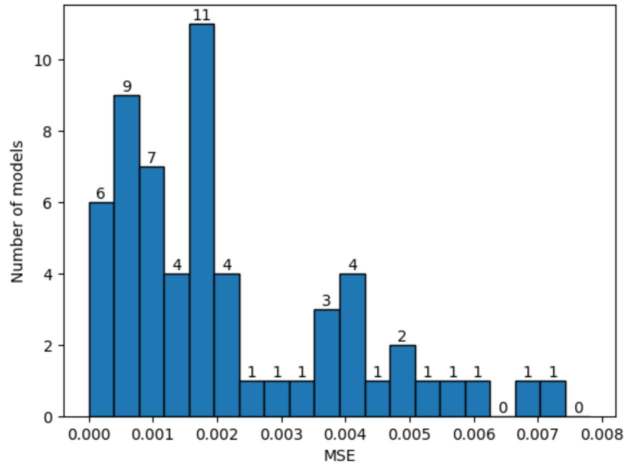

Figure 8 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in 4 hours

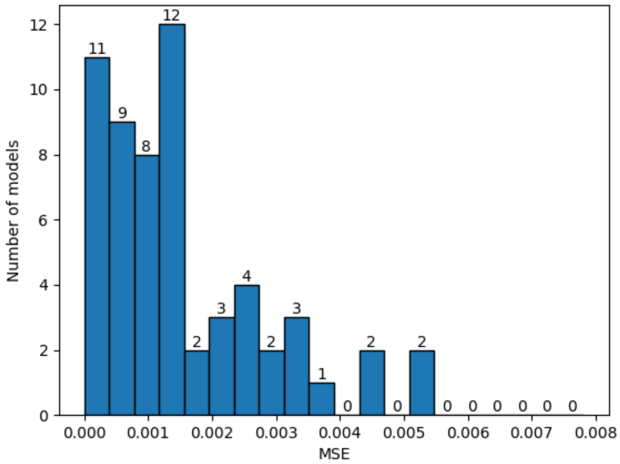

Figure 6 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in 2 hours

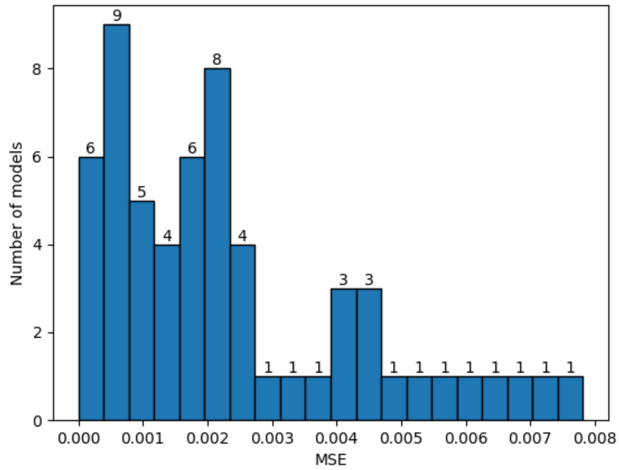

Figure 9 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in 5 hours

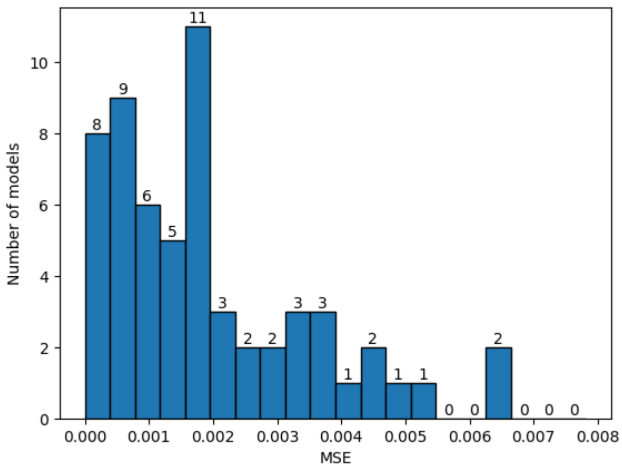

Figure 7 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in 3 hours

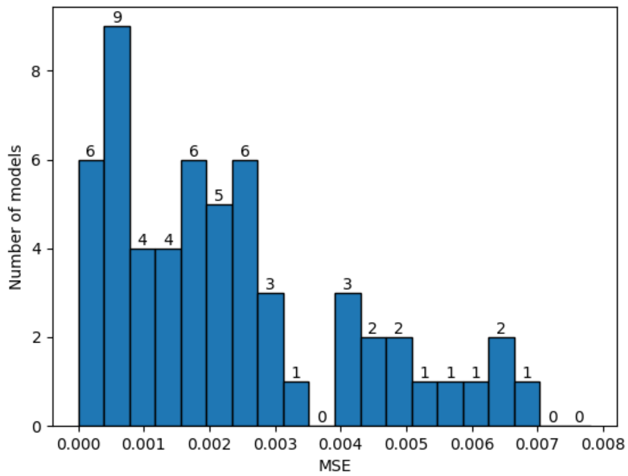

Figure 10 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, 6 hours) for all stations in 6 hours

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Distribution of MSE values for biLSTM models (3 features, adjusted 24/6 previous hours) is presented in Fig. 11–16 hour by hour.

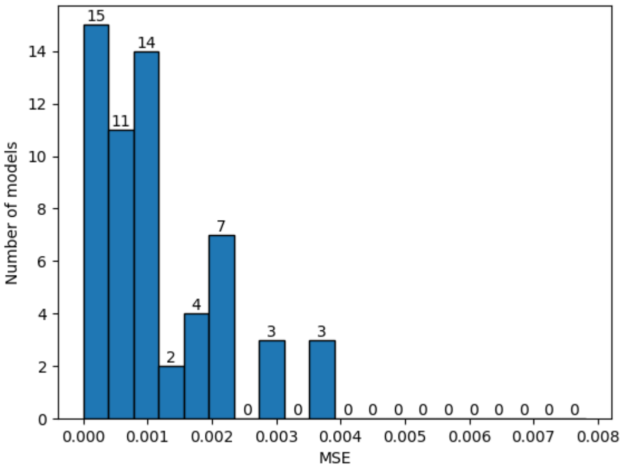

Figure 11 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in an hour

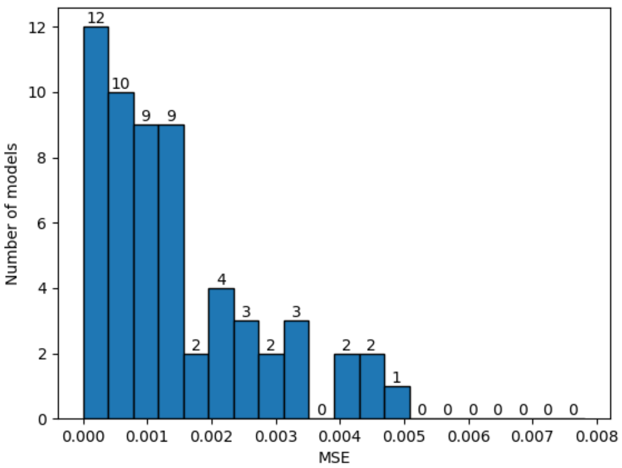

Figure 12 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in 2 hours

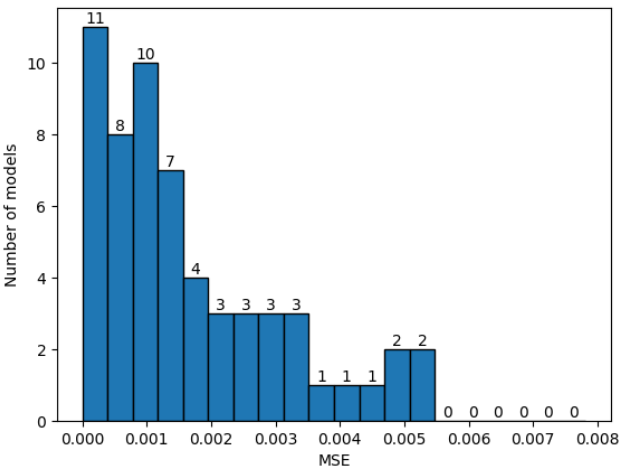

Figure 13 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in 3 hours

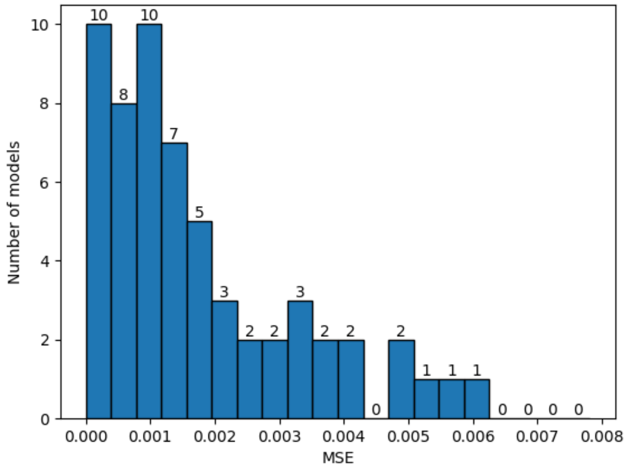

Figure 14 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in 4 hours

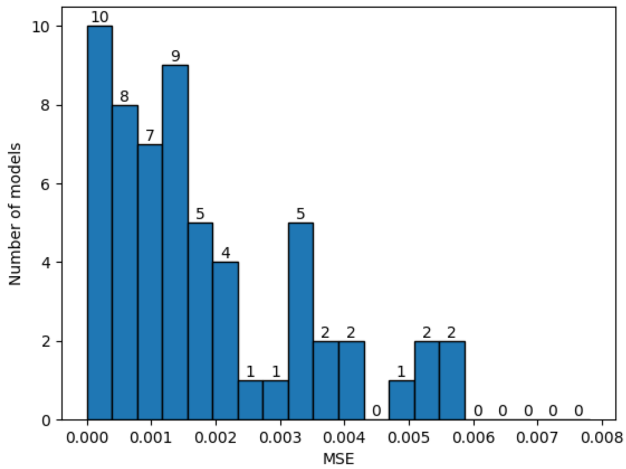

Figure 15 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in 5 hours

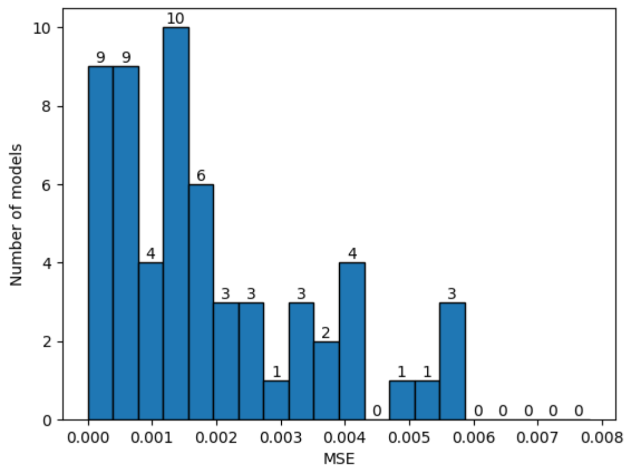

Figure 16 – Histogram visualizing distribution of MSE values obtained by biLSTM models (3 features, adjusted 24/6 hours) for all stations in 6 hours

Each histogram in Fig. 5–16 represents data for an hour.

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Histograms were built with a step computed as 0.00821 (maximum observed value of MSE), divided by 21 to create 20 intervals of MSE values.

Results, representing values of MSE, MAE, RMSE (accuracy), R^2 (informativeness), for each of 59 stations were aggregated in Table 1 by computing average values of each indicator for all models being investigated.

Table 1 – Average results of traffic prediction by different models

Model characteristics	MSE	MAE	RMSE	R^2
LSTM (1 feature, 6 hours)	0.002908	0.032192	0.049139	0.818415
biLSTM (1 feature, 6 hours)	0.002125	0.027964	0.041744	0.863663
biLSTM (3 features, 6 hours)	0.001924	0.026616	0.039862	0.873622
biLSTM (3 features, 24 hours)	0.001636	0.024937	0.036757	0.884319
biLSTM (3 features, adjusted 24/6 hours)	0.001631	0.024942	0.036556	0.891

As absolute values of each model performance evaluation indicator may not completely reflect a relative difference in values for some stations even when normalized, results obtained by biLSTM models with different characteristics were compared to base LSTM model (1 feature, 6 hours) for each station. The results were computed as percentage of these comparisons. Average obtained values of the indicators are presented in Table 2 grouped by biLSTM models with different characteristics (number of input features and length of time period).

Table 2 – Average relative results of traffic prediction by different models compared to LSTM model

Model characteristics	Relative MSE, %	Relative MAE, %	Relative RMSE, %	Relative R^2, %
biLSTM (1 feature, 6 hours)	26.41	12.54	14.61	6.02
biLSTM (3 features, 6 hours)	32.69	16.72	18.43	7.19
biLSTM (3 features, 24 hours)	30.9	22.45	22.06	8.65
biLSTM (3 features, adjusted 24/6 hours)	43.26	22.24	25.26	9.41

6 DISCUSSION

Average results (Table 1) computed over all 59 stations demonstrated that biLSTM models with 3 features and input time period set to 24 hours for 56 stations or to 6 hours for 3 stations allowed to decrease MSE by 43.91 % compared to base LSTM models and MAE by 22.52 %. Informativeness of models increased by 8.87 % on average. So average results of final models emphasize significant improvement in terms of all model performance evaluation indicators.

biLSTM models with input time period of 24 hours allowed to decrease MSE by 14.97 %, MAE by 6.31 %, RMSE by 7.79 % and increase informativeness by 1.22 % compared to biLSTM models with shorter period. Usage of relevant stations as 2 additional input features allowed to decrease MSE by 9.46 %, MAE by 4.82 % and RMSE by 4.51 % compared to biLSTM model with 1 input feature on average. Informativeness of these models was higher by 1.15 %.

Comparison of results demonstrate that bidirectional architecture of LSTM models allowed to decrease MSE by 26.93 %, MAE by 13.13 %, RMSE by 15.05 %, and to increase R^2 by 5.53 %.

However average results do not reflect all broadness of information about efficiency of models. Despite data normalization adjusting input data to the same interval (traffic varies from station to station), values of MSE, RMSE, MAE and R^2 significantly differ from station to station. In some cases, average results can't distinguish improvements for some stations. These cases are characterized by low error if compared to the majority of stations. That's why even significant decrease in such an error may be unnoticed. So, it was important to analyse not only average absolute results of each indicator but its distribution in general, hour by hour and relative results as well.

Therefore, relative changes of indicator values between stations were considered, using base LSTM model as a basis for comparison. In this case difference in values of indicator is computed as percentage. Having percentages for each station and each indicator, it was possible to compute average (Table 2) results. In this case results represent relative values, so difference between error levels for various stations does not affect results. It makes possible to compare results between different architectures and structures of models.

In general results in Table 2 are close to the results in Table 1. But biLSTM (3 features, 24 hours) has relative MSE of 30.9 %, and percentage of change between its value in Table 1 and the same value of base LSTM equals to 43.74 %. It emphasizes significant change, taking into account that all other indicators for all other models have difference in values less than 1 % and only in one case it is slightly higher. Such a difference is explained by the worst case, when biLSTM (3 features, 24 hours) was worse than base LSTM model. It impacts on average relative value in Table 2 but it is impossible to detect such a situation in Table 1, as absolute value of MSE for this station is lower than for other stations. It is additionally emphasized by values of RMSE and R^2. At the same time even the worst value of accuracy obtained by resulting model was better than the one obtained by base LSTM model. So, usage of static input interval in some cases can reflect in results worse than base LSTM model. It makes application of more complex model unnecessary, so its usage for certain station in the case of this dataset or some stations in general is in doubt. But biLSTM models with adjusted input time period have more stable results. It means that resulting biLSTM models allow to obtain better results in terms of MSE, MAE, RMSE, R^2 not only in general but also for individual stations.

Histograms were used for comparative analysis of two biLSTM models with 3 features both but with different length of input time period: with static length of 6 hours and with dynamic adjustment. Distribution of results in terms of MSE according to Fig. 3–4 comes to our notice

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that dynamic adjustment of input time period length for biLSTM models allows to improve obtained results by slightly moving distribution towards less values of error. It additionally underlines and corroborates statements made using average results.

When distribution of MSE is analysed hour by hour, it is noticeably that values of MSE are increasing hour by hour for both variants of biLSTM model. The curve representing changes in columns of histogram is becoming right-skewed as a result. So, the bigger the number of hour is, the lower prediction accuracy is.

But detailed comparison of distribution of MSE for biLSTM models with static input period of 6 hours and with dynamic input period hour by hour comes to our notice some differences. Comparison of Fig. 5 and Fig. 11 demonstrates that there are slightly better results in the first case (Fig. 5). It is noticeable when values in each column for both variants of models are compared from left to right. Number of models (stations) for the first variant is slightly bigger for left intervals and otherwise. But when histograms for the next hours are compared between both variants of models, the trend is different. Dynamic adjustment of input time period (actually between 6 and 24 hours) allowed to decrease MSE in reverse to the first statement. So, the first statement is completely true only for the first hour of prediction.

Therefore, in cases when predictions are made for some number of hours in the future but accuracy of predictions for the first hour is critical, input time period should be decreased and static length of 6 hours should be used. When it is not critical, length of input time period should be adjusted dynamically at the stage of the method described in chapter 3. At the same time, it is worth noting that value of $auto_{\min}$ enables to impact on this choice in an appropriate way.

CONCLUSIONS

The problem of traffic prediction was investigated in the paper. Modern traffic prediction methods are characterized by the complexity of models created. These models have large number of input features, require complete system of traffic measuring stations for spatial recognition based on road system in a city. However, not all cities have complete system of traffic measuring stations. Otherwise data may be inaccessible. Besides, resource restrictions should be taken into account for models created. Therefore, this powerful toolkit is not applicable to all practical cases where traffic is predicted.

Method for traffic prediction was proposed in the paper. This method is applicable under data and resource restrictions. It is based on biLSTM models with additional input features determined by other stations in a city considered relevant. These stations create a subset of the most informative stations selected by ensembles of decision trees using Random Forest method. When real-time predictions are made, data should be collected from different stations. The proposed prediction procedure is based on agent-oriented principles. It represents all stations by software agents. Every agent collects data for its target station, uses trained model for predictions and requests data of relevant stations from corresponding agents. These requests can be realized in parallel. Input time period length is proposed to set using autocorrelation data as a stage of the proposed method.

Experimental investigation was conducted on traffic data taken in Madrid from 59 measuring stations. The obtained results demonstrate significant improvement in traffic prediction using models, created by the proposed method, in terms of accuracy as well as informativeness. Improvement was achieved in terms of MSE (the value is 43 % lower compared to base LSTM model), MAE (22 % lower), RMSE (25 % lower) and R^2 (8–9 % higher). Besides, improvement in all indicators for biLSTM models compared to base LSTM was corroborated as well as for additional input features determined by traffic data of other measuring stations and increasing input time period. Experimental investigation demonstrated that in cases when predictions are made for some number of hours in the future but accuracy of predictions for the first hour is critical, the method should be adjusted to decrease input time period.

Models created by the method application have more optimal number of input features compared to the known models, therefore need less data and do not require complete system of city stations for all roads. It enables to apply these models under city traffic data and resource constraints. The proposed solutions provide high informativeness of obtained models with accuracy level which is significantly higher than accuracy of LSTM models in particular.

The scientific novelty of the obtained results is in the proposed method of traffic prediction.

The practical significance of the obtained results is in the created and trained models enabling to predict traffic at measuring stations for the next 6 hours based on the previous 24 hours or 6 hours in some cases.

Prospects for the further research are to integrate the proposed method for air pollution prediction.

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МЕТОД АГЕНТНО-ОРІЄНТОВАНОГО ПРОГНОЗУВАННЯ АВТОМОБІЛЬНОГО ТРАФІКУ В УМОВАХ ОБМЕЖЕНОСТІ ДАНИХ ТА РЕСУРСІВ

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АНОТАЦІЯ

Актуальність. Проблема прогнозування автомобільного трафіку в місті пов'язана з розв'язанням одночасно і завдань переміщення в місті, і визначення забрудненості повітря в місті. Сучасні моделі прогнозування мають надмірну складність при використанні для окремих станцій, потребують великої кількості станцій спостереження, тривалого періоду спостереження зокрема у випадку погодинного прогнозування. Тому існує потреба в створенні відповідного метода, який дозволить подолати ці обмеження. Об'єктом роботи є автомобільний трафік у місті.

Мета роботи – розробити метод прогнозування автомобільного трафіку, який дозволить створити моделі для визначення трафіку за станціями у майбутньому в умовах обмеженості даних та ресурсів.

Метод. У статті запропоновано метод агентно-орієнтованого прогнозування автомобільного трафіку в умовах обмеженості наявних даних і обчислювальних ресурсів. Даний метод ґрунтується на використанні двонаправлених LSTM моделей з вхідними ознаками, якими є дані, отримані від агента, що відповідає станції прогнозування, та від агентів, що представля-

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ють інші інформативні станції у місті, які обираються на основі використання ансамблів дерев рішень за допомогою методу Random Forest. Довжина вхідного часового інтервалу в методі обирається на основі даних автокореляції.

Результати. Експериментальне дослідження проводилося на основі даних про трафік у місті Мадрид, використовуючи дані, зібрані за 59 станціями спостереження. У результаті застосування створених на основі запропонованого методу моделей було отримано підвищену точність прогнозування, яку було підтверджено зменшенням значень MSE, MAE, RMSE, та підвищену інформативність порівняно з базовими LSTM-моделями.

Висновки. Отримані в результаті проведеного дослідження моделі відрізняються оптимальною кількістю вхідних ознак порівняно з відомими, не потребують використання цілісної системи станцій у місті на всіх автомобільних дорогах. Це дозволяє використовувати дані моделі в умовах обмеження ресурсів та обмеженої доступності даних про трафік у місті. При цьому забезпечується достатньо висока інформативність створених моделей з придатним для застосування на практиці рівнем точності прогнозування.

КЛЮЧОВІ СЛОВА: трафік, прогнозування, часовий ряд, LSTM, двонаправлена LSTM.

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