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Research Article

Prediction of IoT Traffic Using the Gated Recurrent Unit Neural Network- (GRU-NN-) Based Predictive Model

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Prediction of IoT traffic in the current era has attracted noteworthy attention to utilize the bandwidth and channel capacity optimally. In this paper, the problem of IoT traffic prediction has been studied, and solutions have been proposed by using machine learning method ARIMA and learning time series algorithms such as LSTM and gated recurrent unit (GRU-NN) based on neural networks. The proposed GRU-NN predicts the traffic on the basis of transfer learning. The advantage of the GRU-NN over LSTM is also highlighted by solving the problem of gradient disappearance. The proposed GRU-NN memorizes the traffic characteristics of the IoT environment for a long time which eventually helps the system to forecast the upcoming traffic from the existing traces of the traffic. The proposed GRU-NN makes use of the transfer learning technique to handle the problem of insufficient IoT traffic data along with the gradient boosting training method for achieving better accuracy in predicting the network traffic in the IoT environment. The results reveal that the proposed GRU-NN model outperforms the other traffic predictors in terms of statistical performance evaluation parameters such as MAE, RMSE, MRE, and MSE. The results show that the GRU-NN provides the most accurate predictions followed by the LSTM predictor and then ARIMA and other approaches taken up for the comparative study.

1. Introduction

The Internet-of-Things (IoT) traffic is impacted by the regular changes in the IoT devices, their topology, the switching of the channel links during transmission, and the dynamic change of the connectivity of the devices to the internet. A major driver for the success of IoT networks is the prediction of upcoming traffic to handle the channel utilization and resource utilization optimally [1]. The factors that determine the health of the IoT network are cost and energy, and the accurate prediction of traffic can effectively save cost and energy. To prevent congestion on IoT channels and to improve the consumption of IoT resources, IoT traffic prediction and controlling are very important aspects for addressing. The prediction of IoT traffic can forecast the changing characteristics and tendencies of IoT traffic in advance [2]. The accurate forecasting of traffic can certainly allow the IoT users to avail the uninterrupted services [2]. Hence, it is mandatory to suggest a model that can forecast the IoT traffic in advance in an accurate manner. The Internet of Things (IoT) offers a plethora of interesting applications. One of the potential uses is in the sphere of healthcare, where data linked to healthcare are monitored by smart devices and transmitted to medical specialists. Wireless sensor network made up of smart healthcare monitoring devices records certain health indicators and sends them to a local personal digital assistant (PDA), which might be a smartphone or a bespoke device. Eventually, data are forwarded to a backend server through the internet. Remote monitoring in the healthcare industry is now feasible, thanks to Internet-of-Things- (IoT-) enabled gadgets, which have the ability to keep patients safe and healthy while also allowing clinicians to provide superior treatment. As contacts with doctors have grown easier and more efficient,

it has also improved patient involvement and satisfaction. Furthermore, remote monitoring of a patient's health helps to shorten hospital stays and avoid readmissions. IoT has a huge influence on lowering healthcare expenses and increasing treatment results.

In the near future, traffic generated by IoT devices will increase tremendously, and the requirement of resources will also increase eventually. IoT channels have to deal with the futuristic traffic demands and must provide QoS to the users [3]. Therefore, effective utilization of network bandwidth, cloud resources, and available channels is crucial for the IoT environment. This can be achieved by forecasting the upcoming traffic on the channels well in advance accurately. In the IoT environment, there are important issues that require advance prediction of incoming traffic: (i) demand for high transmission rate, (ii) minimum energy usage by saving battery life and by using channels optimally [4], (iii) minimal latency during wired or wireless communications [2], and (iv) optimal utilization of data-intensive and computational resources. The solution to all these issues is efficient prediction of traffic which can certainly address the aforementioned issues.

This paper explores different kinds of predictors and proposes the GRU-NN-based predictor which gives better accuracy in predicting real-time traffic in the IoT environment. The predictors considered for the study are compared with the proposed GRU-NN for the prediction of IoT traffic. The traffic predictors in IoT are widely used to save power by integrating traffic predictors in switches and handoff mechanisms. With the increase in IoT traffic, the demand for the computational and data resources is increasing. The cost of using these resources also increases exponentially. The prediction of traffic can save energy and cost optimally if the predictor produces the results accurately. If the IoT traffic can be projected precisely, the bandwidth can be used optimally, the need for processors in core switches can also be reduced, and the channels can be allocated effectively for forwarding the IoT traffic to intended nodes.

The accurate predictions can also assist in congestion control over the channels, allocation of bandwidth, utilization of resources, detection of anomaly, and reduction in network latency. With the emergence of internet applications such as YouTube, Google Meet, Microsoft Teams, Zoom, and Netflix, video traffic has also been increasing tremendously. There are many state-of-the-art techniques that can predict the traffic, but still, there is a scope for improvement in the existing techniques and a room for exploring new techniques which can handle dynamic video traffic on channels and satisfy the needs of the IoT users. Furthermore, it is challenging to detect and prevent network abuse with the growing IoT traffic at rapid rate and due to diversity in networks.

The objective of the research study is to explore the traffic predictors suitable for IoT applications. The characteristics of the predictor should include accurate prediction of unseen traffic, lower computational complexity, lower space complexity, and lower consumption of power.

The following are the primary contributions of our study in this paper:

(i) The existing techniques are explored and implemented in order to make a comparison of the existing methods with the proposed GRU-NN method. A detailed comparison with respect to accuracy of results is presented in the paper.

(ii) To use the computing resources optimally and to diminish the computational complexity, a GRU-NN is proposed which is more efficient than LSTM; it is able to store long-term state with lesser complexity. GRU-NN can significantly enhance the training efficiency by remembering the states.

(iii) For the problem of insufficient data of IoT devices and unavailability of historical data, a transfer learning model has also been introduced in this paper. By learning from the accumulated data from IoT channels, the transfer learning (TL) method allows the predictor to get trained from accumulated data and the application of the TL-based model in the local domain.

(iv) Statistical performance evaluation metrics are used to verify the accuracy of the proposed GRU-NN with other conventional predictors.

This paper is organized into five sections. The paper begins with the introductory material where background details are highlighted, need of this research study is mentioned, and contributions and objectives are clearly stated. The next section provides details on the existing work similar to our research study and also highlights the research gaps. The third part elaborates the proposed GRU-NN-based predictive model. The next section provides details on the obtained results and comparative study. The last part of the paper concludes the work and result outcomes of the GRU-NN-based predictive model.

2. Related Work

The quick development in IoT traffic promotes huge research advancements in the field of the prediction of network traffic. IoT requires improved and proficient ways to deal with the immense and dynamic traffic [2]. The traffic prediction literature is surveyed as demonstrated in this section.

Abdellah et al. [2] proposed an ANN to predict IoT traffic and to improve the accuracy of IoT traffic projection. The predictive accuracy of the model has been calculated with statistical techniques. Compared to the other predictors, the MSE performance function has demonstrated the best prediction accuracy of the proposed method, and according to comprehensive study and simulation, MAPE has demonstrated the best prediction accuracy for the packet identifiers. Lopez-Martin et al. [3] introduced a new deep learning architecture that can be used to solve the supervised regression issue. It is based on an additive network architecture comprising learning blocks which works with the gradient boosting technique. The results of the proposed new model have been compared with a variety of emerging methods and significantly enhance prediction performance

metrics as well as training/prediction processing times. In terms of machine learning methodologies, Mozo et al. [4] used the CNN to anticipate short-term changes in the quantity of traffic that goes through a data center network. The experimental results have shown that CNN's nonlinearity outperforms ARIMA's results.

In [2], authors presented a model that targets base stations using spatiotemporal information from nearby cellular stations. These features are used to predict traffic over time using deep learning techniques such as 3D convolutional networks. The technology employed yielded promising findings that outperformed those of existing traffic forecasting systems. Artificial intelligence (AI) techniques are required for a successful 5G network. The application of machine learning (ML) to traffic forecasting has been successful. In [5], a deep learning-based technique is explored to implement the traffic predictor using time series. The predictive accuracy is measured with the RMSE score and the mean absolute percentage of error (MAPE) as the MAE score. In [6], NARX time-series recurrent neural networks have been utilized to anticipate IoT communication. Three neural network training techniques have been used to test the predictability, trainlm, traincgf, and trainrp, with MSE, RMSE, and MAPE performance evaluators. As compared to others, the model forecast with the trainlm training module shows the best accuracy, while the model projected with the trainrp training module has the least predictive accuracy than other models, depending on the outcomes of the simulation.

In [7], the research is revolved around the deep neural framework for single-step time series forecasting that combines wavelet transformations (WTs), 2D CNNs, and LSTM- stacked autoencoders (SAEs). According to the findings, the suggested model has surpassed the other models in terms of prediction accuracy. In [8], the authors provided a brief overview on the contextual and existing literature on deep learning methods with possible features. The study has also provided an overview of a few strategies and technologies that assist in deploying deep learning techniques on mobile devices for the prediction of traffic in wireless networking. In [9], authors projected a feature selection strategy based on random forests to tackle the tough challenge of acquiring spatial data. The Gini score is used to indicate the spatial relationship between intersections in a data-driven network graph. The experimental results have suggested that using random forest feature selection and the RCF model, traffic forecast accuracy can reach 90%.

In [10], authors have demonstrated three deep learning models for forecasting the network traffic. CNN and RNN models with raw traffic data are proficient for accomplishing accurate outcomes when compared to two other baseline solutions. To forecast forthcoming transfer learning (TL) and congestion in the network, Tang et al. [11] introduced a unique deep learning architecture including a TL prediction method. To create a unique intelligent channel assignment technique, a deep neural-based predictive model with partially overlapping channel allocations is investigated. Finally, the paper suggested a unique intelligent channel assignment

technique that smartly prevents future blocking of channels with huge traffic and quickly provides relevant channels to SDN IoT. The results of the simulation reveal that the approach is far superior to traditional algorithms for the channel assignment. The study in [12] uses machine learning approaches to accurately identify the IoT network. They have deployed the multivariate classifier for segregating IoT and non-IoT traffic. Every IoT device is assigned to a certain IoT device class in the second step. The model's overall IoT categorization accuracy has been analyzed as 99.281%.

In [13], authors described a machine learning method by examining streams of packets delivered and received for distinguishing the kind of IoT devices. They created a model to represent IoT device network activities based on the collected data. The network traffic created can be distinguished by various IoT devices by using the t-SNE approach to represent the data. The compliance data of the network will then be utilized to train distinct ML classifications to envisage which IoT device is responsible for the network traffic. The experiments have shown promising results with an overall accuracy of 99.9% on the test dataset. In [14], authors introduced the system identifier (SysID), a system for automatically classifying device features based on network data. They employed GA to identify key features in various protocol headers and then used ML classifiers for device identification with over 95% accuracy. In [15], authors presented a framework that extracts network flow characteristics to identify the type of traffic. The experimental analysis has shown a device-type recognition accuracy of 94.5%, traffic-type classification accuracy of up to 93.5%, and abnormal traffic detection accuracy of up to 97%. In [16], the authors proposed a spatiotemporal sensing approach with deep neural networks as a network traffic prediction method. This is crucial for traffic forecasting to include shorter-range dependent modelling. The proposed prediction approach has outperformed three current methods in simulation.

Alqudah and Yaseen [17] discussed different ML approaches for traffic projections. Rapid IoT traffic and AI development necessitate new methods for detecting intrusions, analysing virus activity, and categorizing IoT traffic. The proposed methods are able to achieve the predictions of dynamic traffic. In [18], the authors made use of reinforcement learning for the network traffic predictions. Markov decision process and Monte Carlo methods are used to predict network traffic. They evaluated the effectiveness of their mechanism using real network traffic. In [19], authors addressed wireless network traffic's spatiotemporal properties and constructed a recurrent neural network to predict network traffic. The experts not only have considered the long-term dependence on traffic flows but also the short term. In [20], the authors used optical data center networks and LSTM technique for traffic flow predictions. The proposed method has outperformed the existing traditional algorithms according to experimental results. In recent years, artificial neural network (ANN) and machine learning along with statistical analysis have been used in various areas of research such as medicine, engineering, mathematics, meteorology, neurology, and economics [21, 22].

With the great success of deep learning, researchers are exploiting the usage of deep NN algorithms for traffic prediction. However, the question about which type of deep neural network is best for traffic flow prediction remains unanswered. To overcome the gradient vanishing problem, certain RNN structures, such as LSTM and GRU, have been designed to overcome the problems of RNN-based models. Hence, we are also making use of the GRU-NN method in our proposed work to predict the traffic more accurately by overcoming the drawbacks of conventional deep learning models.

3. Prediction Framework for IoT Traffic

To predict the IoT-based traffic, this manuscript proposes a GRU-NN predictor based on collaborative transfer learning. The GRU-NN predictor works in three stages: data processing, training of the model, and transfer phase. The data processing stage assists in preprocessing of the data, and it converts the continuous data into discrete records to suffice the input needs of the GRU-NN model. The training phase is the most important phase of the GRU-NN predictor. In this manuscript, a GRU-NN model is proposed to train the model. The transfer phase is also a vital phase which transfers a huge amount of offline data to the training module to handle the issue of insufficient data of IoT traffic in an online mode. Finally, the GRU-NN traffic predictor is framed.

3.1. Data Preprocessing Phase. The data processing begins with the collection of the continuous data at regular time interval t and then converts the continuous stream of data into discrete chunks. The discrete data are distributed into a fixed time window of m size, and then the traffic data are acquired as $A = [a1, a2, a3, a4,......, a - 1, an]$. The data *'an'* of the last n time is the output B of the predictor. Next, the sequence of the data is distributed into the training test set, and then the dataset for the predictor training test is attained.

3.2. Model Building Module. In the traffic predictor, the second phase is of prime importance which builds the model. It begins with the designing of a single-layered GRU structure. The single-layered structure helps in reducing the time complexity as it takes lesser time in the optimization of the factors. The overall GRU-NN is a three-layered architecture, the very first layer represents the input layer, and the number of neurons in the input layer is equal to the dimension of the input IoT traffic. The 2nd layer is the hidden layer, and the number of neurons in this layer is decided by the empirical study of the obtained output. The last layer represents the output, and this layer finally predicts the output or predicts the traffic.

3.2.1. Training Module. The training of the model refers to the square loss function optimization. This training module minimizes the loss function value with the adjustment of the weight matrix. Generally, the gradient method is used for the

optimization of the weight matrix, but this may result in a local optimal solution. We have used the ion filter method to escape from this problem of the local optimal solution.

3.2.2. Fine-Tuning Process of the Model. The fine-tuning of the network structure enhances the generalization ability of the model, resolves the problem of overfitting, and helps to minimize the model training time. In order to handle the issue of inconsistent and imbalanced data, normalization procedure takes place before the execution of the activation function. Although the imbalanced data distribution has been resolved in [12], these techniques are not capable to save the loss of data. Two learning parameters are introduced to handle this problem which are termed as β and γ.

The training of the GRU-NN method can be described as the optimization of GRU-NN parameter θ so that the variance between the actual and the predicted value of the method can be reduced as far as possible as shown in equations.

$$\theta = \text{argmin}_\theta \frac{1}{N} \sum_{i=1}^{N} \text{loss}(A_i, B_i, \theta), \qquad (1)$$

$$\text{loss} = \frac{1}{N} \sum_{i=1}^{N} (A_i - \widehat{A}_i)^2, \qquad (2)$$

where $A_1, B_1, A_2, B_2, ..., A_N, B_N$ are the training datasets and θ is GRU-NN's weighting parameter. The loss function of the GRU-NN is the mean square error, and $\widehat{A}_i$ is the forecasted value.

A dropout layer has been added before the hidden layer.

$$p_j^l \sim \text{Bernoulli}(p), \qquad (3)$$

$$\widetilde{a}^l = p_j^l * a^l, \qquad (4)$$

where p_j^l is the probability of Bernoulli as shown in equation (3) and is specifically designed for IoT traffic data, $\widetilde{a}^l$ is the randomly discarded value on the basis of input a^l with probability p_j^l as shown in equation (4), and the output is zero of discarded neurons. The normalization mean for a sample is represented as shown in the following equation:

$$\widehat{a}_i = \frac{a_i - \mu}{\sigma}, \qquad (5)$$

where $a = \{a_1, a_2,..., a_d\}$ is the IoT data, μ is the expected input of IoT data a, and σ is the standard deviation of the input data a. This procedure can resolve the issue of discrepancies in data, but the direct input can be represented in the following equation:

$$B_i = \gamma_i \widehat{a}_i + \beta_i. \qquad (6)$$

The model training involves the optimization of the square loss function. This module optimizes the loss function value using the weight matrix. In our problem statement, the gradient technique is used to avoid the problem of local optima.

4. Results and Discussion

4.1. Experimental Results. This section provides insights into the evaluation metrics considered for the research study. In order to evaluate the prediction capability of the proposed GRU-NN method, the statistical error analysis techniques are utilized.

(1) Mean absolute error (MAE) is the average of all absolute errors, and the formula is as follows:

$$MAE = \frac{1}{n} \sum_{a=1}^{n} |z_a - z|, \tag{7}$$

where n depicts the number of errors, $\sum$ depicts the summation of all values, and $|z_a - z|$ is the absolute errors.

The MAE score is presented in Figure 1 obtained by the proposed GRU-NN and other conventional techniques such as ARIMA (autoregressive integrated moving average), LSTM (long short-term memory), and VAR (vector autoregression). The results show that the proposed GRU-NN forecasts the IoT traffic with least error and highest accuracy, and it outperforms the traditional techniques such as ARIMA, VAR, and LSTM.

(2) Root mean square error (RMSE) shows the standard deviation of the forecasted errors, and the formula is as follows:

$$RMSE = \sqrt{\frac{\sum_{a=1}^{n} (z_a - \widehat{z}_a)^2}{N}}. \tag{8}$$

(3) N is the number of nonmissing data points, a represents the variable, z_a are actual observations of time series, and $\widehat{z}_a$ represents predicted time series.

The RMSE scores are presented in Figure 2, and it can be observed that the proposed GRU-NN shows best results with respect to the RMSE score and outperforms the other three techniques taken up for the research study.

(4) Mean squared error (MSE) summarizes the prediction ability and forecast accuracy of the proposed GRU-NN model. It is calculated using equation (9) and is shown in Figure 3.

$$MSE = \frac{1}{n} * \sum (\text{actual} - \text{predicted})^2. \tag{9}$$

In order to exhibit the viability of the proposed GRU-NN method-based predictor in this paper, three comparative techniques are taken up which are benchmarked methods for forecasting the traffic. Compared to the VAR-based traffic prediction algorithm, GRU-NN performs very well as it has the ability to forecast by retaining relevant information in its layers. ARIMA is capable to process short-term time series, whereas the GRU-NN can consider long-term series also. Statistical continuity also shows that LSTM does not
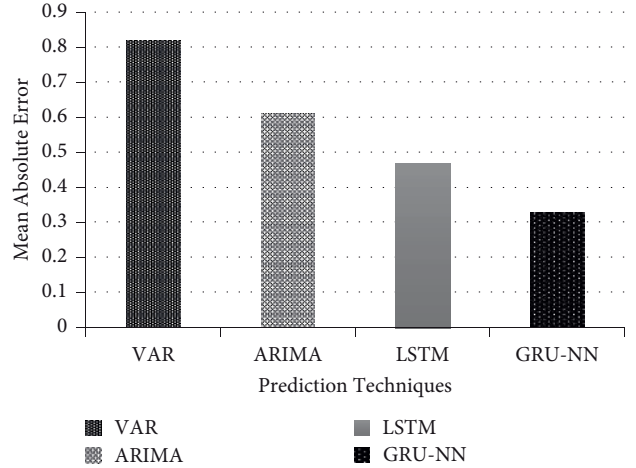

Figure 1: MAE score obtained by the proposed and other models.
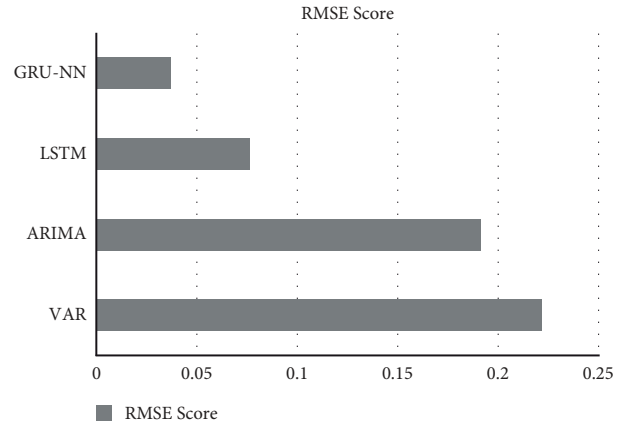

Figure 2: RMSE score obtained by the applied algorithms.
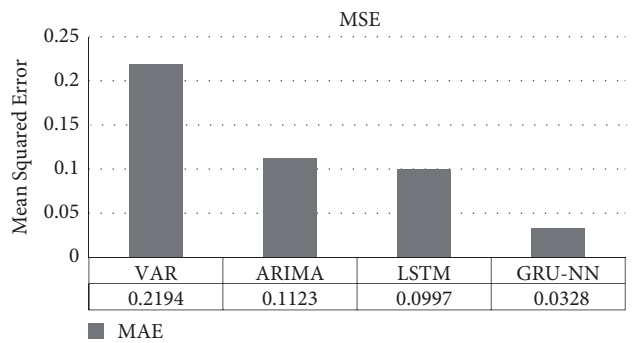

Figure 3: MSE scores obtained by the applied algorithms.

support nonlinear fitting capability. LSTM performs well in forecasting traffic, but sometimes, the relevant information is lost in the hidden layers. The proposed GRU-NN is well suited on time-series data and is able to control data of IoT-based network traffic very well. Both methods LSTM and GRU-NN perform well for forecasting the IoT traffic, but the GRU-NN gives more accurate results as compared to LSTM as shown in the results.
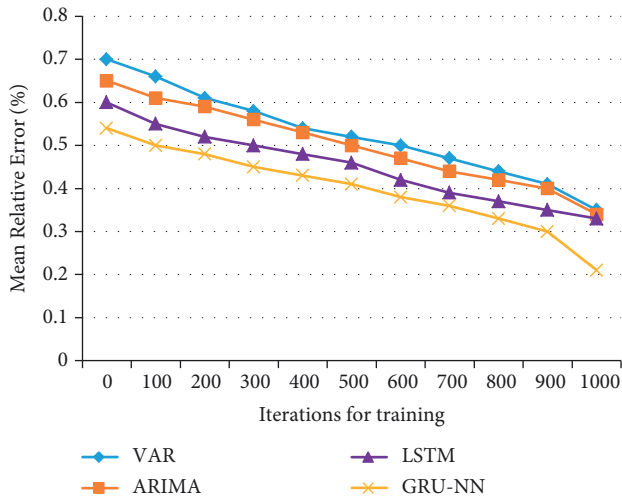
Figure 4: MRE values obtained by diverse techniques in defined iterations.

For verifying the space complexity and efficiency of convergence of the algorithms, the iterations for the training set are defined similarly for the algorithms considered for the research study, and it is observed from Figure 4 that the GRU-NN outperforms other techniques with respect to MRE scores. MRE is the ratio of the absolute error of a reading to the measurement being taken and is expressed in % as it has no units. However, in the beginning, the relative error of the proposed GRU-NN is higher, and it gradually decreases. The other techniques also behave in the same manner, but the GRU-NN shows the best performance with respect to the MRE scores.

5. Conclusions

In order to handle IoT traffic, it is inevitable to predict the traffic in advance for better utilization of resources and bandwidth. The IoT devices have attracted great attention in this decade, and traffic prediction is mandatory to enhance the channel capacity and to reduce the network latency. In this paper, the problem of IoT traffic prediction has been examined, and the GRU neural network-based solution has been proposed. Three well-established traffic predictor techniques have also been studied and considered for the comparative study. The proposed GRU-NN predicts the traffic accurately as depicted in results based on statistical performance evaluation metrics such as RMSE, MAE, and MSE. The advantage of the GRU-NN over LSTM is that it is capable of solving the problem of gradient disappearance and loss of information in hidden layers. The proposed GRU-NN memorizes the long correlation and other traffic characteristics of the IoT environment. The proposed GRU-NN outperforms ARIMA, VAR, and LSTM for predicting the IoT dynamic traffic. In a future study, a hybrid method for traffic forecasting will be researched upon, which may improve the performance efficiency of existing predictors by combining the characteristics of different methodologies.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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