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GREEN DIGITAL OPERATION AND MAINTENANCE TECHNOLOGY OF POWER EQUIPMENT BASED ON DEEP LEARNING

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Abstract. In order to solve the problem of low accuracy in traditional digital operation and maintenance of power equipment, the author proposes a research on green digital operation and maintenance technology of power equipment based on deep learning. The author first analyzed the text characteristics and segmentation difficulties of work orders, summarized seven types of entities, and manually annotated 3452 work orders to form a training set, Secondly, pre train the BERT module using relevant equipment testing and fault analysis reports to obtain power word vectors, Then use the BiLSTM module to predict entity labels, Finally, the CRF module was introduced to optimize the prediction labels and conduct Chinese entity recognition experiments on 1000 work orders. The experimental results indicate that: Compared with LSTM, BiLSTM, and BiLSTM-CRF models, the BERT BiLSTM-CRF model has better entity recognition performance in power primary equipment operation and maintenance work order texts, with an F1 value of 85.7%, which is 11.6%, 7.3%, and 4.8% higher than the other three models, respectively. This system can effectively improve the work efficiency of operation and maintenance personnel, reduce their communication costs, achieve efficient management of on-site equipment, and assist enterprises in achieving production goals of improving quality and efficiency.

Key words: Power primary equipment operation and maintenance work order, BERT model, Bidirectional Long Short Term Memory Network, Conditional random airport

1. Introduction. In the construction process of the new power system, we will vigorously promote the research and development of ultra-high voltage power equipment and the application of power electronic devices, and bear the long-term impact of impact energy loads such as wind power and photovoltaic in the new power system. Conducting on-site operation and maintenance tests on them will incur a significant cost [1]. Applying digital twin technology to the field of state perception and operation and maintenance of ultra-high voltage power equipment in the "dual high characteristic" new power system should overcome numerous key links [2]. Multi domain simulation of high-voltage power equipment involves structural analysis models, flow field analysis models, multi-body dynamics models, fatigue analysis models, acoustic analysis models, electromagnetic simulation models, and electronic heat dissipation analysis models [3]. This physical model realizes the virtual construction and visual analysis of high-voltage power equipment, and also has the ability to simulate and calculate multiple physical fields. It can achieve real-time simulation calculation and dynamically display the distribution status of electrical/thermal/mechanical/fluid multiple physical fields through external loads and boundary conditions [4]. Physical space mainly includes performance, functionality, and structural strength; The digital space mainly includes models, algorithms, and visualization [5]. Flow field and electric field distribution can be effectively achieved in twin bodies, while visualizing and analyzing vibration, deformation, fluid, electric field potential current, fatigue, and life information.

Since the launch of the Power Production Management System (PMS) in the power grid, the operation and maintenance work order data of primary power equipment has shown explosive growth [6]. These data contain rich information on the health of power assets, but they are mainly stored in unstructured text format, which is difficult to effectively utilize. Therefore, it is particularly important to structure unstructured operation and maintenance work orders. With the development of named entity recognition technology in natural language processing, possible solutions have been provided for the above-mentioned problems.

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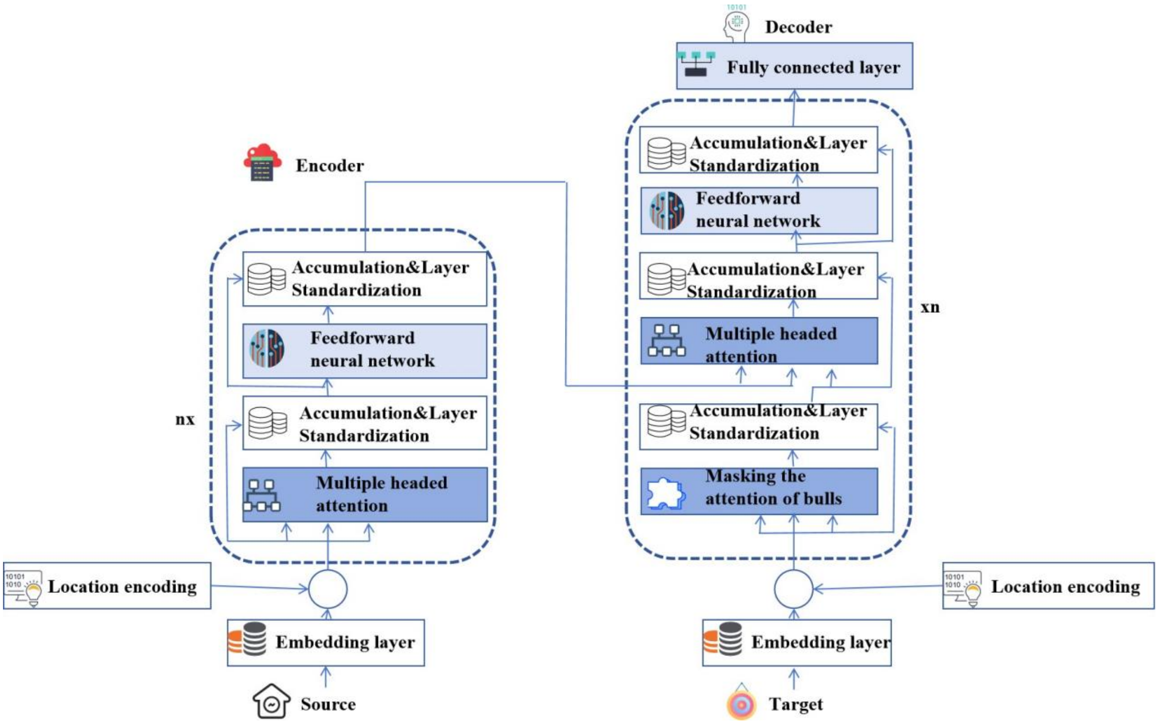

Fig. 1.1: Power Equipment for Deep Learning

Through the research and development of intelligent control technology for power equipment, a digital operation and maintenance management system for equipment is formed to enhance the information and intelligent management capabilities of key equipment in the installation process, testing and experiments of enterprises, assist in enterprise transformation and upgrading, complete delivery on time, and improve the core competitiveness of enterprise production activities [7] (Figure 1.1).

2. Literature Review. In the new situation of economic development, the construction of the power grid remains at a high level. As the core equipment of power grid construction, power equipment is a prerequisite for ensuring the safe and stable operation of the power grid [8]. Against the dual background of the "dual carbon" goal and digital transformation strategy, power equipment is a key component of the power industry and an important support for achieving carbon reduction and digital transformation goals [9]. As a leading enterprise in the power industry, strengthening the management of power equipment suppliers is of practical significance for power grid enterprises to operate themselves and collaborate with suppliers to achieve their goals [10]. On the basis of analyzing the value chain of power grid enterprises, the author aims to build an evaluation system for power equipment suppliers from the perspective of value chain synergy, based on the simulation results of the system dynamics model, optimization suggestions for power equipment management under this evaluation system are obtained, providing a basis for the evaluation and management of power equipment suppliers in power grid enterprises. Gilani, H. When selecting green water plants, one of the best methods is to use sustainable selection methods. In addition, the model solves the problem of improving all communications, choosing the right equipment for the treatment plant by choosing different equipment, and controlling the water loss [11]. Zahedi, R. believes that the demand for power equipment in power grid enterprises is complex and vast, and they face a large and uneven number of power equipment suppliers. The evaluation and selection of suppliers in the process of power equipment management become the key to selecting equipment. Building an efficient and reasonable power equipment evaluation system is conducive to comprehensively and effectively feedback information and behavior of power equipment suppliers in the big data environment, thereby forming data resources and helping power grid enterprises to do a good job in power equipment supplier management [12]. With the operation and development of enterprises, the activities of realizing value appreciation in the value chain extend from product production activities to services and other activities. Mehmet Mithat ü ner focuses on organizing internal audits of power grid enterprise business processes from a value chain perspective, with value creation, value-added activities, and corresponding business processes as the main audit objects, in order to achieve value added for the enterprise [13]. Ali, Z. predicts the value chain operation of power equipment manufacturing enterprises from multiple aspects such as production, marketing, and service, effectively improving the accuracy of business risk prediction for power equipment manufacturing enterprises [14].

At present, named entity recognition technology has begun to penetrate into the field of electricity. The author constructed a model based on BERT BiLSTM CRF for unstructured operation and maintenance work order data of primary power equipment, and achieved named entity recognition for operation and maintenance work orders of primary power equipment [15]. Firstly, the text characteristics and segmentation difficulties of operation and maintenance work orders were analyzed, and seven types of entities were summarized: "equipment name", "equipment voltage level", "equipment line", "equipment substation", "equipment damaged parts", "equipment maintenance situation", and "equipment maintenance time". More than 3400 work orders were selected for entity annotation, forming a training set; Then, a BERT model suitable for the power field was pre trained, and BiLSTM was used as the entity label prediction layer and CRF was used as the processing layer for the global optimal solution of the label. Together, a power equipment operation and maintenance work order entity recognition model was constructed; Finally, a high accuracy recognition experiment for work order text entities was completed.

3. Method.

3.1. Overall demand analysis. In order to make the functions of the platform more in line with production reality, the designers started from the daily work of municipal station operation and maintenance management personnel, fully considered the business needs of three types of roles: decision-making, management, and execution. Based on 3D visualization and web related technologies, the key production elements of individual and various production equipment in the station were mapped to the 3D visualization scene, making it closely related to the management of daily production processes, and achieving dynamic monitoring and digital management of the entire life cycle of assets and equipment in the station. As shown in Figure 3.1, the system needs to achieve the following functional requirements.

Integrating multi-dimensional data with 3D models can dynamically display the overall and constituent units of the model, and users can query information such as process flow, individual size, and spatial position through interaction with the model.

3.1.1. Information on the use and maintenance of basic electrical equipment. Textual information on electronic equipment operation and control activities is obtained from 350,000 work order records in the company's PMS. The author only considers the operation and maintenance data of main transformers, isolating switches and circuit breakers for three-phase main electrical equipment of 120kV, 210kV and 510kV. After cleaning the data, more than 12000 work orders were selected as data.

3.2. Characteristics and segmentation difficulties of operation and maintenance work order text. After analyzing the contents of the above work notes, compared to the general calculations, we found that the work notes for the operation and maintenance of the main electronic equipment have the following characteristics.

1. The content of the operation usually includes information such as electronic equipment, equipment name, equipment line, electrical equipment, non-functional equipment, cleaning equipment, cleaning time, etc. However, because of the differences in writing supervision, there is a difference in the structure and execution of the content of the staff and the work order.
2. Due to the different types of equipment failure and the difference in cleaning process, the length of work order is very different. According to the available data, the shortest worksheet can be 11 words, and the longest is 354 words. Difficulty in the segmentation of work orders for the operation and maintenance of the main electrical equipment is:

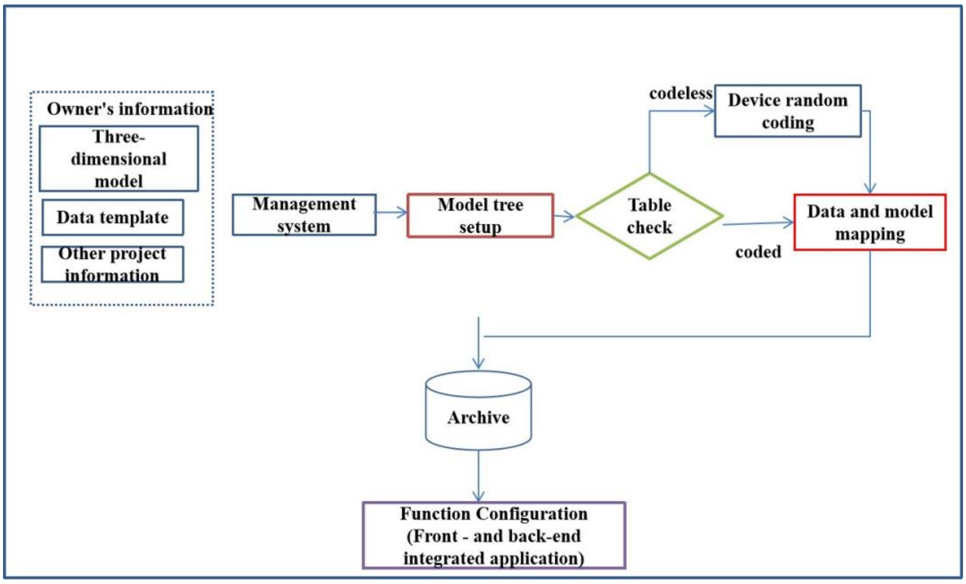

Fig. 3.1: Overall Business Requirements

(a) Due to the different writings of work and maintenance workers, there are some differences in their descriptions for the same product or equipment, for example, "main transformer" is abbreviated as "main transformer";
(b) for numerical data in the text of the work order, such as voltage level "120kV" and device model "capacitor model BAMH2", it is necessary to rely on the elements statement of the meaning for the conclusion of the enterprise proportion;
(c) For various work orders, the description of the maintenance of explosives and equipment is long and there are many devices, inconsistencies, and unclear segmentation boundaries, so the model should be able to be generalized.

3.3. BERT BiLSTM CRF based operation and monitoring operation certification standard. By analyzing the above mentioned O&M work orders and segmentation problems, the author developed an O&M work order recognition model based on BERT BiLSTM CRF.

First, the BERT module is prepared to use the interference measurement and error analysis of three main types of electrical equipment: the main transformer, circuit breaker and isolation; Second, to get the correct vectors, enter the text of the operation order into the pre-prepared BERT module in the sentence; Then use BiLSTM to extract the local features of the words and predict the object names; Finally, the correlation between the adjacent labels is done by CRF to get the best prediction for classification [16].

3.4. BERT module. In natural language processing, the term embedding is used to obtain a low-level representation of a language, i.e., a vector representation of the language.

Currently, mixed language models include Word2Vec and GPT. But these models have some difficulties in recognizing the work of the original equipment and management work force. The Word2Vec model generates static word embeddings and cannot represent polysemy. GPT, on the other hand, is a one-way language that cannot accept the content of that language.

The results of the BERT model reduce the above problems by identifying character-level and language-level features to improve the representation of language vectors and improve the accuracy of the model from previous training [17]. Therefore, the author chooses the BERT model to capture the message vectors of operations and control operations. To improve the accuracy of the model, the author first trained the BERT model.

Specifically, each word input by BERT is represented by the superposition of three vectors: Token Embed-

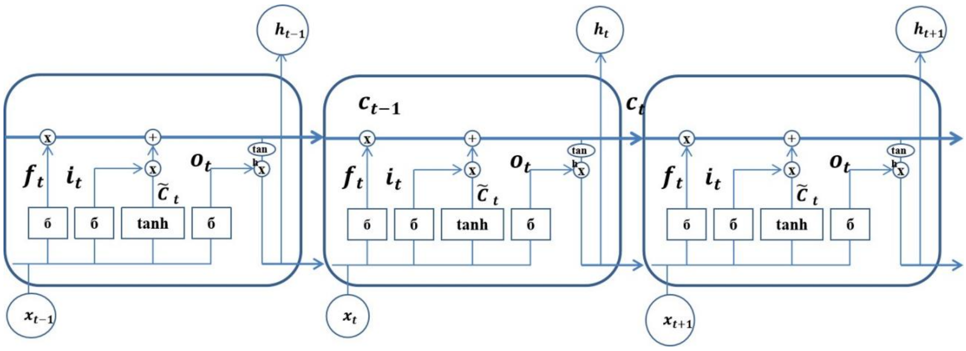

Fig. 3.2: Unit structure of LSTM

ding, Seg Element Embedding, and Position Embedding, which means word embedding, sentence embedding, and position embedding. In the figure, [CLS] is used to mark the beginning of a sentence, and [SEP] is used to mark the boundary between two sentences.

Its basic structure is a combination of various transformer encoders. The encoder has a multihead self-guided mechanism, a residual module, a normalization module, and a feedforward neural network.

In the encoder, the most crucial part is the self attention mechanism, which is expressed as:

$$Attention(Q,K,V) = Softmax(\frac{QK^T}{\sqrt{d_k}}) \tag{3.1}$$

In the formula, Q, K, and V represent the query vector, key vector, and value vector, respectively, calculated by the word embedding vector through linear transformation matrices W_Q, W_K, and W_V. d_k is the dimension of the key vector, used to adjust the inner product of QKT to prevent gradient instability during training due to excessive inner product. The multi head self attention mechanism is a linear combination of self attention mechanisms, which can enable the model to learn more relevant information in different representation subspaces, increasing the diversity of model information sampling. Its formula is expressed as equation 3.2.

$$MultiHead(Q,K,V) = Concat(head_1, \cdots, head_n)W^0 \tag{3.2}$$

$$head_i = Attention(QW_i^Q, KW_i^K, VW_i^K) \tag{3.3}$$

After each self attention module, residual and normalization processing (Add&Norm) is required on the results to improve the vanishing of model gradients and accelerate network convergence. Finally, link the feedforward neural network to enhance the model space and consolidate the original encoding information.

3.5. BiLSTM module. Due to the inability of fully connected neural networks to mine contextual semantic information of input sequences. Therefore, the author proposes Recurrent Neural Network (RNN), which has a certain memory function but suffers from gradient vanishing and exploding problems [18]. Subsequently, Long Short Term Memory (LSTM) networks introduced threshold mechanisms to address the issues of long-term dependencies and gradient vanishing [19]. The unit structure of LSTM is shown in Figure 3.2.

The core of LSTM is a forget gate, input gate, output gate, and a memory unit. Forgetting Gate f_t determines how much historical information affects C_t. The input gate i_t determines how much current input information affects C_t. The output gate o_t controls how much information is visible to the outside world, that is h_t. The calculation formula for updating the unit status of LSTM is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3.4}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{3.5}$$

$$\widetilde{C_t} = tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3.6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{3.7}$$

$$C_t = f_t C_{t-1} + i_t \widetilde{C_t} \tag{3.8}$$

$$h_t = o_t tanh(C_t) \tag{3.9}$$

In the formula, σ represents the sigmoid excitation function, W represents the weight matrix, b represents the bias vector, h_{t-1} represents the output of the LSTM unit at the previous time, and x_t represents the input at the current time.

Due to the inability of unidirectional LSTM to obtain text features through posterior input information, the author uses Bidirectional Long Short Term Memory (BiLSTM) network to extract text features and improve the model capability of power entity recognition.

3.6. CRF module. BiLSTM extracts text features based on context, outputs the score for each character corresponding to each label, and outputs the label with the highest score for that character as the final label. However, there is a label mismatch issue. Therefore, a Conditional Random Field (CRF) is introduced to handle the dependency relationship between labels and obtain the optimal prediction sequence, aiming to improve the accuracy of prediction as much as possible.

For any input sequence $X = (x_1, x_2, \cdots, x_n)$, assuming that the corresponding output label sequence trained by BiLSTM is $Y = (y_1, y_2, \cdots, y_n)$, the score function is:

$$S(X,Y) \sum_{i=1}^{n} (A_{y_{i-1},y_i} + P_{i,y}) \tag{3.10}$$

In the formula, n is the number of characters, A_{y_{i-1},y_i} represents the transition score matrix between adjacent character labels in the text, and $P_{i,y}$ is the y_i label score of the i-th character in the text. The probability of predicting sequence Y is:

$$P(X,Y) = \frac{e^{s(X,Y)}}{\sum_{\widetilde{Y} \in Y_X} S(X, \widetilde{Y})} \tag{3.11}$$

In the formula, $\widetilde{Y}$ represents the true annotation sequence, and Y_X represents the set of all possible label sequences. Finally, the set of labels with the highest score will be used as the optimal label output.

3.7. Value Chain Theory Analysis. Analyzing the operational status of enterprises from the perspective of value chain, dividing enterprise activities according to their value appreciation status, and analyzing value activities can provide a more comprehensive understanding of the enterprise's business process, as well as the conditions and problems faced by each link. It can discover how to improve the quality and efficiency of each value link activity, thereby enhancing product value, maximizing enterprise value, and promoting sustainable development of the enterprise [20].

3.8. Experimental Preparation.

3.8.1. Annotation System and Datasets. The common named entity recognition annotation systems mainly include BIO, BIOES, BIOES+and other modes, and the author adopts the BIO annotation system. In this system, B (Began) represents the first character of an entity word, I (Inside) represents the middle and last characters of an entity word, and O (Outside) represents a non entity word. Filter out 3462 work orders from the operation and maintenance work order data source, and use annotation tools to manually annotate the text using seven types of labels: "Voltage Level", "Equipment Name", "Line Name", "Transfer for Sta", "Damage Part", "Repair Condition", and "Time".

Finally, the annotated results are transcoded into the BIO annotation system and divided into training and testing sets in a 7:4 ratio. An example of text annotation for operation and maintenance work orders is shown in Table 3.1.

Table 3.1: Example of Work Order Text Annotation

Character	Dimension	Label	Dimension
Li	B-EquipmentName	shut	I-EquipmentName
1	I-EquipmentName	hair	O
2	I-EquipmentName	heat	O
7	I-EquipmentName	Follow	B-RepairCondition
Septum	I-EquipmentName	Tracking	I-RepairCondition
leave	I-EquipmentName	measure	I-RepairCondition
open	I-EquipmentName	temperature	I-RepairCondition

Table 3.2: Training Environment Configuration

Operating system	Linux
CPU	Intel(R)Xeon(R)Silver4114
GPU	TeslaV100
Python	3.5

3.8.2. Evaluation indicators. The author uses recall rate R, accuracy rate P, and F_1 values to evaluate the performance of the model. The calculation method for each evaluation index is as follows:

$$P = \frac{T_P}{T_P + F_P} \tag{3.12}$$

$$R = \frac{T_P}{T_P + F_N} \tag{3.13}$$

$$F_1 = \frac{2PR}{P + R} \tag{3.14}$$

In the model, T_P represents the number of actual positive events and predicted positive events, F_P represents the number of negative events and predicted positive events, and F_N represents the number of actual positive events and predicted negative events.

3.8.3. Experimental Environment. Build an experimental environment based on the PyTorch platform, and the specific training environment configuration is shown in Table 3.2.

3.8.4. Experimental parameter configuration. During the training process, the Transformer encoding part of the BERT model has 10 layers, 10 self attention mechanisms, and an output of 400 dimensions. Other specific hyperparameters are shown in Table 3.3.

4. Results and Discussion. In order to verify the recognition performance of the model used in the operation and maintenance work order text of primary power equipment, 1200 work order texts from the test set were used to test the model. The specific experimental results are shown in Table 4.1.

According to Table 4.1, compared with LSTM, BiLSTM, and BiLSTM-CRF models, the BERT BiLSTM-CRF model has better entity recognition performance in power primary equipment operation and maintenance work order texts, with an F1 value of 85.7%, which is 11.6%, 7.3%, and 4.8% higher than the other three models, respectively. Compared to the LSTM model, the BiLSTM model considers the posterior input in terms of input sequence, so the results are slightly better. Compared to the BiLSTM model, the BiLSTM-CRF model has added a CRF module, which can better handle the dependency relationships between labels, so the evaluation index is slightly higher. Compared to the BiLSTM-CRF model, the BERT BiLSTM-CRF model uses the BERT module, which can enhance the model's representation ability in the power field through pre training and output higher quality word vectors, thus improving the evaluation indicators.

Table 3.3: Experimental Parameter Settings

Parameter	value
Number of Transformer Layers	10
hidden_dim	210
optimizetr	Adam
learning_rate	0.0021
max_sequence_dim	400
batch_size	30
dropout	0.6
epoch	60

Table 4.1: Test set test results

Model	P	R	F_1
LSTM	0.814	0.706	0.742
BiLSTM	0.810	0.775	0.785
BiLSTM-CRF	0.835	0.804	0.808
BERT-BiLSTM-CRF	0.863	0.825	0.857

5. Conclusion. The author presents research on green digital marketing and electronic device technology based on in-depth research. Three-dimensional production equipment and maintenance, the operation and maintenance of workers can help improve productivity and maintenance, stabilize the station, improve business level and quality control. It helps achieve the goals of efficient management of equipment, maximum utilization of resources, automation of operations and management, and optimization of business operations. At the same time, it provides important knowledge for the development of other digital industries and future car maintenance.

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