# Research on deep reinforcement learning-based power equipment event extraction technique

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## ABSTRACT

Power equipment public opinion events can affect all aspects of the power industry, including equipment failures, power supply interruptions, environmental impacts, and policy changes. Through public opinion event extraction, electric power companies and related government agencies can monitor and analyze public concerns and feedbacks in real time, quickly respond to potential problems, improve equipment management and maintenance, increase power supply reliability, and reduce operational risks. In this paper, we propose a deep reinforcement learning-based public opinion event extraction framework for electric power equipment, and design a reward function based on the recognition of trigger words and the detection results of related event elements, and finally, through comparative experiments, we can see that the extraction results of the proposed framework are better, and it can meet the requirements of public opinion event extraction for electric power equipment.

**Keywords:** Deep reinforcement learning, power devices, reward functions, trigger words

## 1. INTRODUCTION

Opinion event extraction is a natural language processing technique designed to automatically identify, extract and summarize information related to specific events, topics or public opinion concerns from large-scale text data. The purpose of public opinion event extraction is to help institutions and organizations better understand, monitor and respond to public views, needs and sentiments. By extracting information related to specific events, topics or concerns from large amounts of text data, opinion event extraction helps track public opinion trends in real time, identify potential crises or opportunities, improve public relations strategies, enhance crisis management, and support decision-making. This not only helps to improve an organization's reputation, but also helps to better meet the needs of the public, thus enhancing the interaction and trust between the organization and its audience. Therefore, public opinion event extraction is of strategic importance in today's information society.

Conducting public opinion event extraction on power equipment is crucial for the power industry. It helps to monitor in real time public opinion information related to power equipment, energy supply and renewable energy, including equipment failure events, equipment commissioning events, equipment research project establishment events, grid equipment bidding and procurement events, power equipment accidents, environmental impacts, and so on. By extracting public opinion events, power companies and relevant government agencies are able to identify potential problems more quickly, improve equipment maintenance and management, increase power supply reliability, and better meet energy demand. In addition, it helps to improve communication between the public and the power industry, increase transparency, increase the acceptance of sustainable energy, and create a more favorable environment for the development of renewable energy and power equipment. Therefore, public opinion event extraction for power equipment is important in ensuring reliable power supply, improving efficiency and promoting sustainable development.

For the problem of how to extract the event information from the complicated text, some researches have also proposed very promising methods for application. Commonly used methods for public opinion event extraction include traditional machine learning and deep learning methods. Traditional machine learning methods usually include rule-based and feature-engineering approaches, as well as models such as support vector machines (SVM), maximum entropy, and decision trees. Deep learning methods, on the other hand, include convolutional neural networks (CNN), recurrent neural networks (RNN), Transformer, etc., which extract event information from large-scale textual data through end-to-end learning. In addition, the pre-trained language models such as BERT and GPT are also widely used for opinion event extraction, which can provide

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more generalized token representations and improve the performance of the extraction task. Different methods have their advantages and limitations in different application scenarios, and choosing the right method usually depends on the needs of the specific problem and the available data.

Using traditional machine learning and deep learning methods in solving public opinion event extraction requires the construction of complex feature engineering, and the results are sometimes not very good. In this paper, we propose a deep reinforcement learning-based framework for power equipment opinion event extraction, specifically, the process includes two steps, which are trigger word recognition and related event element detection. In the first step, the intelligent body in the framework scans the words in the sentence in a front-to-back order, and one scan is called one behavior of the intelligent body, and in each behavior, the event type is assigned to the current word using a greedy strategy. If the current word is recognized as a trigger word (not of type "None"), it proceeds to the second step of BiLSTM-CRF (conditional random field) sequence tagger for detection of relevant event elements, which learns generic features based on verb and noun events in advance, and later migrating to a small-scale event labeling dataset in the power domain to post-train the network, a robust power event tagger is obtained and applied to subsequent tasks. The detection results from the second step can be used as a basis for calculating the behavioral rewards in the first step, as well as to help with modeling updates for the reinforcement learning environment. In the training process of the model, this paper trains an optimal event extraction strategy by adding a deep evaluation model and using an Actor-Critic based deep reinforcement learning method. Finally, this paper demonstrates the effectiveness of our proposed framework through experiments.

## 2. RELATED WORK

Early extraction methods relied on pattern matching, required experts to design templates, and were difficult to migrate between domains[1,2]. Traditional machine learning methods such as SVM[3] and maximum entropy[4] treat event extraction as a classification task and require complex feature engineering. In recent years, researchers have turned to deep learning models such as CNN, Recurrent Neural Networks, Graph Neural Networks, and Transformer Encoders to perform event extraction. In particular, pre-trained language models such as ELMOp[5], GPT[6], and BERT[7] are able to generate more generalized labeled representations, better initialize model parameters, and improve performance generalization across different tasks.

Although neural network approaches have shown some effectiveness in event extraction, they are severely constrained by the scarcity of labeled data in practical applications[8,9]. For example, CNN can effectively enhance event extraction, but the most typical drawback of CNN models is that they cannot capture the dependencies between distant words well, and the pipelined execution of the two subtasks, event detection and argument extraction, faces the problem of error propagation. In addition, although the Transformer-based model can significantly improve the performance of event extraction, it is not necessarily applicable in real-world scenarios due to its serious data-dependency and arithmetic resource-dependency problems, while high-quality hardware devices are not easily available in real-world scenarios due to financial constraints and other factors. In addition, the Transformer structure position information encoding is an artificially designed index, and the position encoding does not have transformability in the semantic space when doing linear transformation of word vectors, and it is unreasonable to add this position encoding to the word vectors, so it cannot characterize the position information well. The size of the labeled data volume is also a reason that limits the application of neural network methods to event extraction, e.g., in many domains such as biomedicine, finance, news, law, and electricity, the available labeled data is very limited by a number of factors including data sensitivity, confidentiality requirements, the complexity of the labeling effort, and the high cost[10-12]. In addition, small languages and widely used English also face the challenge of insufficient labeled data. At the same time, existing event extraction datasets are usually small and unevenly distributed, further limiting the applicability of the methods and posing significant challenges to existing techniques[13].

The use of deep reinforcement learning for opinion event extraction can avoid extensive feature engineering work, and on the one hand, it can adapt to variable text data and complex contexts, continuously optimize extraction strategies based on real-time feedback, and autonomously learn the best way to extract event information from large-scale text data[14-16]. On the other hand, deep reinforcement learning's ability to automate decision making, its potential to deal with complex contexts, and its flexibility make it likely to perform well in event extraction for specific domains or tasks[17,18]. In this paper, we target the extraction of public opinion events of electric power equipment in text by constructing a model, recognizing trigger words and event-related elements in text, and training the model based on a deep reinforcement learning framework to effectively extract public opinion events such as failure of electric power equipment, commissioning of equipment, and accidents of electric power equipment.

## 3. METHOD

In this paper, we designed a deep reinforcement learning-based event extraction framework for power equipment public opinion and conducted comparative experiments using CNN-based and Transformer.

### 3.1 Event Extraction Task Definition

The goal of the power equipment public opinion event extraction task is to extract power equipment target events from a large amount of unstructured text, which contains two subtasks: trigger word recognition and event-related element detection. Assuming that the input of the model is text statements $X = (x_1, \cdots, x_t, \cdots, x_N)$, where $x_t(t \in 1, \cdots, N)$is transformed into a real−valued vector $w_t$ after mapping, It contains word embedding, lexical embedding, entity class new embedding and external knowledge embedding, where external knowledge embedding is using public domain news texts as the base corpus.

Putting $w_t$ into the model for electric power setup opinion event extraction, electric power equipment opinion trigger word identification: trigger word is the core unit of electric power equipment opinion event extraction, which clearly expresses the emergence of an electric power equipment opinion event, and the task of trigger word identification is to discover the trigger word in a sentence. If the trigger word exists in the sentence, it is necessary to further determine which event type or types the sentence belongs to. Power Equipment Opinion Event Related Element Detection: identifying all elements from a sentence that contain a power equipment opinion event type, the identification of the elements usually relies on the results of trigger word identification and classification. Each argument element is categorized based on the elements included in the extraction pattern of that event.

### 3.2 CNN

Convolutional neural networks can capture the syntactic and semantic features of sentences well, effectively alleviating the lack of training data. The weight-sharing strategy of CNNs can reduce the training parameters of the network, lower the model complexity, be more adaptable, and reduce the dependence on annotated data, thus extending the model's ability to generalize, which is effective, especially when faced with a new type of event that does not have any annotated data.

CNN-based power equipment opinion event extraction first learns a feature extractor using training data of auxiliary types and randomly initializes the weights of the CNN, after which a CNN model is trained using a small portion of labeled data of the target type and randomly initialized weights to predict the target event type and the old event type. In addition to utilizing a small portion of annotated data for new event types, new event types without any annotations are also identified, and the CNN is utilized to map the structural representations of event triggers and event types onto a shared semantic space, and to migrate the knowledge of the visible event types to the unseen types by minimizing the distance between the two.

### 3.3 Transformer

Different from traditional CNN, RNN and GNN, Transformer's network structure mainly consists of multi-head attention mechanism and feed-forward neural network. The most representative is the BERT model obtained based on the construction of Transformer encoder, whose two-layer bi-directional structure can fully model the contextual information of words to enhance the effect of event extraction.

Transformer model-based extraction of power equipment opinion events can utilize a language-unknown approach to start ("priming") the language model and augmenting the inputs to the Transformer stack language model based on the questions that the model is asked at runtime, nicely compensating for the shortcomings of sparse and noisy data.

The power equipment opinion event extraction task of training a model on a single source language can lead to the same problem of monolingual bias, and a language recognizer method can be spoofed using unlabeled data in the target language to assist in the alignment of cross-language representations. However, the method is not conditioned on class information, and target language samples from one class may be incorrectly aligned with source language samples from a different class. To address this problem, representation learning can be performed using class information from relation and event extraction tasks. Two versions of the representation vectors are learned for each class using the BERT model, and the representation vectors of the relevant classes are aligned to obtain class-aware alignment for cross-language representations, as well as aligning the representation vectors for language-common word kinds (e.g., POS tags and dependencies).

By connecting event types and event-related elements as natural language queries to the input text in the Transformer model, and using the BERT model and the attention mechanism to utilize the rich semantic information in the query, this query extraction paradigm can well capture the semantic relationships between event types, event-related elements, and the input text, and at the same time, it can take advantage of the annotations from the various ontologies available for events.

### 3.4 Deep Reinforcement Learning

In the power equipment public opinion event pumping $w_t$ fetching framework designed in this paper, it is divided into two steps: first, scanning the trigger words in the text statement in the order of front-to-back, splicing the word vector of the trigger word and the word embedding group of the current environment into the state input $s_t$ of the intelligent body, and then assigning the event type to the trigger word according to the greedy policy, and in this way assigning the behavior is called a single action $a_t$ of the intelligent body. through the Performing the action $a_t$ and trigger word $w_t$ of the intelligent body re-splicing the action a_t and the trigger word w_t to form a new representation of the text statement $X = (w'_1, \cdots, w'_t \cdots, w'_N)$; Secondly, detect the event elements related to the trigger word through the BiLSTM-CRF module, and the result $\hat{Y}$ and the true representation $Y$ of the event elements are used in the computation of the reward function. The framework model designed in this paper is shown in Figure 1.

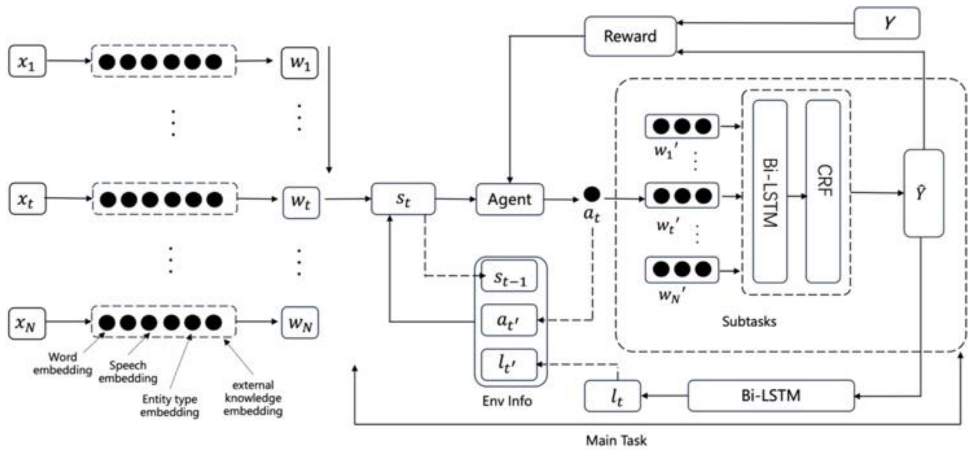


Figure 1. Deep reinforcement learning-based power equipment public opinion event extraction framework.

Through the reward function, the results of event-related element detection can be fed back into the trigger word recognition process. In this paper, based on the design of the reward function, the deep reinforcement learning model is designed with the goal of obtaining the maximum cumulative rewards, which enables the model to extract more accurate results for the extraction of public opinion events of electric power equipment. Among them, the deep reinforcement learning framework designed in this paper is mainly composed of four parts: action A, state S, policy π and reward R. Each part is specified as follows.

(1) Action A

An action $a_t$ is taken at time $t$ to determine the event type of the currently scanned word in the store's equipment opinion events. Each action is selected from a set $A$, where $A = \{None\} \cup T$, None is a "non-triggering word", and $T$ is the set of types of opinion events of the power equipment.

(2) State S

The state $s_t \in S$ at moment $t$ is computed by combining these four pieces of information: 1) the representation of the current word $w_t$; 2) the last non-None getting action $a_{t'}$; 3) the result of the most recent element detection $\hat{Y}_{t'}$; and 4) the state $s_{t-1}$ of the previous moment, which is represented by the following formula.

$$s_t = f(W_s[w_t; a_{t'}; \hat{Y}_{t'}; s_{t-1}]) \tag{1}$$

$f(\cdot)$ is a nonlinear function in deep learning, and $W_s$ is the weight matrix of the model, where $a_{t'}$, $\hat{Y}_{t'}$, and $s_{t-1}$ are used as the environment information for the next intelligent body interaction.

(1) Strategy $\pi$

In this paper, we use a greedy strategy to assign types to scanned words in the process of trigger word recognition, where $\pi: S \rightarrow A$ is the probability distribution of the action, and optimize the parameters in the distribution $softmax(\cdot)$ and the weight matrix $W_\pi$ in the training process.

$$a_t \sim \pi(a_t|s_t) = softmax(W_\pi s_t) \tag{2}$$

(2) Reward R

After the intelligent body takes the action $a_t$, the environment first gives a reward $r_t^b$, and then makes the final reward based on the results of detecting the elements related to the event (i.e., the type of event is judged correctly), where $r_t^b$ is represented as follows.

$$r_t^b = \begin{cases} 0.5, correct\ type \\ 0,\ None \\ -0.5,\ wrong\ type \end{cases} \tag{3}$$

If the action $a_t$ judges that the current word is a non-triggering word, the intelligent body jumps to the next word to continue scanning, otherwise, it uses the BiLSTM-CRF module to detect the event-related elements in the current utterance, and the result is expressed as $\hat{Y} = \{\hat{y}_1, \cdots, \hat{y}_t, \cdots, \hat{y}_N\}$, and compares it with the labeled data $Y = \{y_1, \cdots, y_t, \cdots, y_N\}$, which serves as the basis of the calculation of the final reward, and defines $g(\cdot)$ as the indicator function, which is 1 if the expression it contains is true, and 0 otherwise, and the expression for the calculation of the final reward is.

$$r_t^f = r_t^b \cdot \sum_{i=1}^{N} g(\hat{y}_i == y_i) \tag{4}$$

## 4. MODEL TRAINING

In this paper, the policy function of the reinforcement learning module is designed as a deep learning network, which solves the problem of updating the policy function when the action space is large, and a value function is added, which is also designed using a deep learning network. In order to find the optimal policy, the model is trained in this paper using Actor-Critic. The Actor-Critic algorithm is essentially a policy-based algorithm as the goal of the algorithm is all about optimizing a policy with parameters by additionally learning the value function, which in turn helps the policy function to learn better.

Specifically, at moment $t$, the intelligent body samples the trajectory $\{s_1, a_1, r_1, s_2, a_2, r_2, \cdots\}$ according to the strategy $\pi$. Then, for each step, according to the following equation.

$$\delta_t = r_t + \gamma V_w(s_{t+1}) - V_w(s_t) \tag{5}$$

Where, $\delta_t$ is the time-series difference residual, $\gamma$ is the discount factor, and $V_w(s_t)$ is the value function. Then the strategy function is updated.

$$\theta = \theta + \alpha_\theta \sum_t \delta_t \nabla_\theta \log \pi_\theta (a_t|s_t) \tag{6}$$

Where $\alpha_\theta$ updates the step coefficients and $\theta$ is the strategy function parameter. Here the strategy function is to learn a value function from the data collected by the action $a_t$ interacting with the environment, and then make a judgment on what action is favorable in the current state, which in turn helps the action to make a strategy update.

## 5. EXPERIMENTS

In this paper, we verify and analyze that the proposed deep learning-based reinforcement learning framework can effectively extract power equipment public opinion events through CNN and Transformer comparison experiments.

### 5.1 Dataset

The dataset used in this paper comes from a company's long-term public opinion event collection data on power equipment, including equipment failure events, equipment commissioning events, equipment research project establishment events, as well as grid equipment bidding and purchasing events and power equipment accidents, involving information such as equipment type, event, time, information publisher, product unit involved, project name, time, equipment type, voltage level, and location. In the experimental stage, this paper divides the dataset into three subsets, which are used for model training, validation and testing respectively. The statistical information of the dataset is shown in Table 1.

Table 1. Statistics on public opinion events on electric power equipment.

| Entity type | | Dataset |
|---|---|---|
| | | 20 |
| Training set | Number of entities | 5812 |
| | Number of events | 3576 |
| | Number of sentences | 1583 |
| Validation set | Number of entities | 1697 |
| | Number of events | 1109 |
| | Number of sentences | 576 |
| Test set | Number of entities | 2398 |
| | Number of events | 2289 |
| | Number of sentences | 650 |

### 5.2 Analysis of experimental results

1) Performance comparison of different models.

Table 2. Performance comparison of different models for power equipment public opinion event extraction.

| Methods | P (%) | R (%) | F1 (%) |
|---|---|---|---|
| CNN | 60.18 | 56.28 | 58.41 |
| Transformer | 69.89 | 56.42 | 60.56 |
| Our Method | 68.12 | 58.89 | 62.13 |

In Table 2, P denotes the precision rate, R denotes the recall rate, and F1 is the value calculated based on the precision and recall rate of the classification model. From Table 2, it can be seen that although the model proposed in this paper is slightly lower than Transformer in terms of accuracy by 68.12%, its recall and F1 value are higher, so it can be concluded that the framework proposed in this paper is effective in the extraction of public opinion events on power equipment.

2) Ablation Experiment.

Table 3. Ablation experiments of different models for power equipment public opinion event extraction.

| Methods | P (%) | R (%) | F1 (%) |
|---|---|---|---|
| Method without KBs | 54.45 | 51.28 | 53.67 |
| Method without DRL | 52.43 | 50.21 | 52.47 |
| Method with DRL+KBs | 67.76 | 57.90 | 61.87 |

As can be seen from Table 3, this paper does ablation experiments on deep reinforcement learning framework and external knowledge base respectively, and the effect of ablation experiments on external knowledge base is significantly better than that of ablation experiments on deep reinforcement learning framework. From this, it can be concluded that in the extraction of public opinion events on electric power equipment, the contribution of deep reinforcement learning framework to the extraction effect is greater than the influence of external knowledge base on the extraction effect.

## 6. CONCLUSION

In this paper, we design a deep reinforcement learning-based framework to extract power equipment public opinion events, which avoids the work of constructing complex feature engineering compared to traditional supervised learning methods and deep learning methods. This paper concludes that the proposed deep reinforcement learning framework is effective in the extraction of power equipment public opinion events through comparison experiments with CNN and Transformer models, as well as ablation experiments.

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