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Case Characterization and Discipline Measurement Method Based on Discipline Inspection and Supervision Knowledge Graph

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Abstract: As an important link to realize intelligent discipline inspection and supervision, the term "case characterization and discipline measurement" refers to the automatic extraction of material facts from case description and the conclusion of conformity and nonconformity after comparison in accordance with legal norms. In response to the problem that there was no special method for the task of case characterization and discipline measurement, the paper combined the practical case handling process of the staff and proposed a method of case characterization and discipline measurement based on discipline inspection and supervision knowledge graph. The method uses the knowledge graph as auxiliary information and aligns the entities of regulations and cases using knowledge fusion technology to construct the discipline inspection and supervision knowledge graph. For the newborn case descriptions, named entity recognition technology is used to extract the key elements that determine the verdict outcome. Similar cases were identified with the same discipline breach nature. Then, text classification technology is used to predict the severity of case circumstances. Combined with the disciplinary violation facts, the disciplinary result is given according to the party discipline rules. Experiments were carried out with a dataset of typical cases notified by the discipline inspection and supervision. According to the experimental results, the proposed method shows its validity, which improves the interpretability of case characterization and discipline measurement and fills the field gap.

Keywords: Case Characterization and Discipline Measurement, Knowledge Graph, Natural Language Processing

1. Introduction

In recent years, China has continued to advance the construction of intelligent discipline inspection and supervision. Discipline inspection and supervision organs at all levels are actively exploring comprehensive and strict governance of the party, making full use of information technology tools such as big data and artificial intelligence (AI). The in-depth integration of "Internet+" with discipline inspection and supervision work [1] renders convenient and inclusive legal services. The construction of intelligent discipline inspection and supervision includes building a knowledge graph, case characterization and discipline measurement in the field of discipline inspection and supervision, etc. This aims to provide knowledge access and decision support for anti-corruption work in practice, using knowledge from the fields of law, regulation and previous cases. In particular, the case characterization and discipline measurement involves the automatic identification of the key elements of a case given the case description text. As a result, these key elements could be summarized as highly as possible in line with "X act" and "severity of the circumstances", under the main premise of the legal norm that "X punishment shall be given to X act with minor circumstances". Nevertheless, a high-level summary of discipline breach facts should be considered to accurately define the disciplinary subject, disciplinary offence, severity of the circumstances, etc. In addition, the severity of the disciplinary circumstances is one of the key factors in guiding discipline measurement penalties. However, there are no clear criteria for determining the severity of the circumstances, which makes the task of case characterization and discipline measurement more difficult.

In the field of discipline inspection and supervision, the previous research mainly focuses on knowledge graph construction, similar case recommendation, and charge prediction. A previous study by Liu et al. used regular expressions to obtain legal elements of case descriptions, used a neural network model to learn the importance of different legal elements, and calculated case similarity based on the output of the vectors from the intermediate layer [2]. Although the accuracy of extracting legal elements based on regular expressions is high, the legal elements of different cases are very different, poorly generalized, and time-consuming. Similar case recommendation [3] was considered as a multi-label classification problem to predict case charges. But this method recommends similar cases only based on the prediction results of charges, which has low accuracy. Moreover, there were more irrelevant words in the case text, which affects the accuracy of the charge prediction. Wang et al. constructed a knowledge graph of laws and regulations and conducted a study of automatic Q&A, which answered simple questions related to laws and regulations [4]. The knowledge graph of laws and regulations can provide jurisprudential level support, but the automated Q&A is unable to respond to complex case characterization and disciplinary questions in long texts.

To address the above issues, this paper constructed a characterization and discipline measurement dataset using typical cases notified in the Exposure section of the Central Commission for Discipline Inspection and Supervision website. And then combined with the practical working ideas of judicial staff, this study explored the process and method of case characterization and discipline measurement based on the discipline inspection and supervision knowledge graph. Firstly, the knowledge graph of discipline inspection and supervision was constructed. Secondly, information matching is used for case characterization and discipline measurement work: The first step is that key elements which determined the verdict outcome were extracted from the case descriptions and searched for similar cases and case-related laws in the knowledge graph based on the extraction results. Similar cases were identified with the same discipline breach nature. Next, the severity of the case circumstances was predicted, and discipline recommendations were given in the context of discipline breach facts and in accordance with party discipline and regulations.

2. Case Characterization and Discipline Measurement Method

2.1. Overall Process Architecture

Through the analysis of typical case studies, the present research concludes that entities such as disciplinary subject, disciplinary offence and severity of the circumstances have a decisive impact on case characterization and discipline measurement. Among them, the former two decide the determination of the nature of the violation in the qualitative and quantitative discipline, while the latter two will affect the punishment result of the subject of the violation. Therefore, starting from the aspects of accurately grasping the subject, behaviour and severity of the violation, this paper divides the qualitative and quantitative discipline based on case knowledge graph into two main steps: named entity recognition and classification and prediction of severity of violation. Among them, the purpose of named entity recognition is to extract the elements of violation in case description, and then accurately identify the nature of violation. The prediction step of the degree of disciplinary violation is to learn the degree of disciplinary violation from the punishment results of typical cases. The specific process framework is shown in Figure 1.

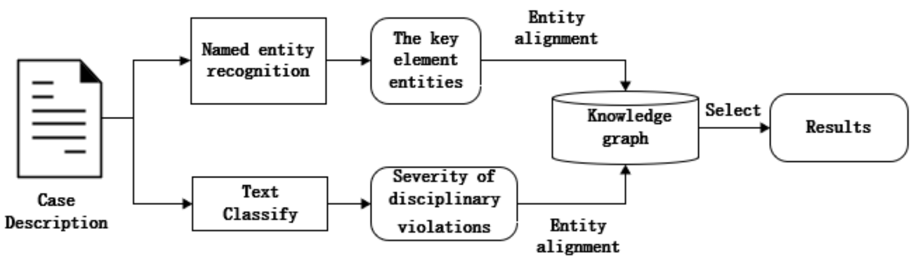

Figure 1. *Process Framework of Case Characterization and Discipline Measurement.*

Knowledge fusion. Guo et al. constructed a case knowledge graph of discipline inspection and supervision based on a large amount of case information, and the content of the knowledge graph is shown in Figure 2, which can provide knowledge access and other services for case characterization and discipline measurement [5]. But the case qualitative quantity needs to be supported by laws and regulations. Therefore, in order to better adapt the knowledge map of discipline inspection and supervision cases to the task of case characterization and discipline measurement, this paper integrated the party discipline regulation into the case knowledge graph.

Data Collection and Processing. In this study, typical disciplinary cases reported in the Exposure section of the

Central Commission for Discipline Inspection and Supervision website were used as data sources. After data sorting, they were divided into entity identification naming datasets and circumstance severity prediction datasets.

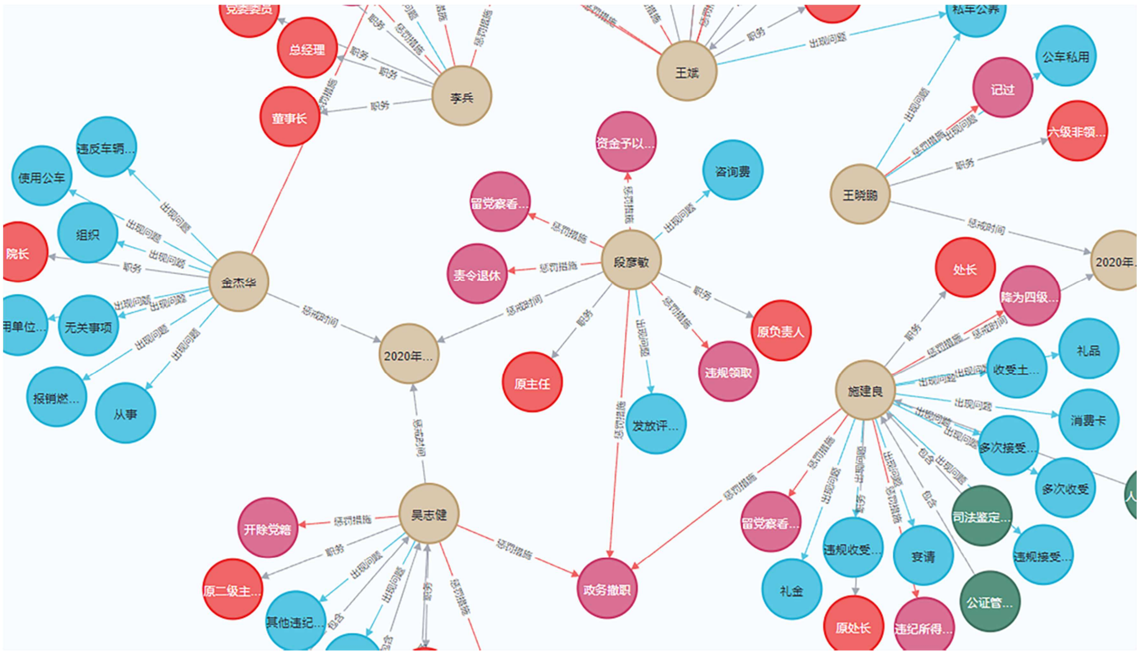

Figure 2. *Partial display of the case knowledge graph.*

Qualification of the Case. In this study, BERT-BiLSTM-CRF entity identification naming was used to extract key elements of the case description, such as disciplinary subject and disciplinary offence.

Case Measurement Disciplinary Judgment. In this study, BERT pre-trained language model was used to learn contextual semantic features of case descriptions and to classify case descriptions into three categories: "minor circumstance", "serious circumstance" and "critical circumstance".

Answer Selection. According to the results of the above entity identification naming and classification prediction, query statement templates were constructed, and case characterization and discipline measurement results were returned, providing case characterization and discipline measurement predictions for new discipline breach facts based on previous cases. The case example is shown in Figure 3.

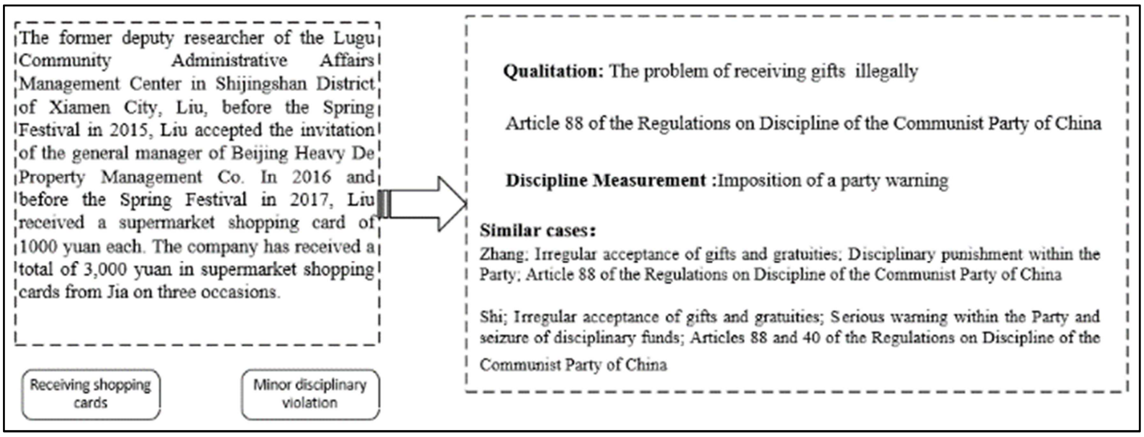

Figure 3. *Case characterization and discipline measurement example.*

2.2. Related Technology Introduction

2.2.1. BERT Pre-trained Language Model

The BERT pre-trained language model [6], known as Bidirectional Encoder Representations from Transformers, uses a bidirectionally trained transformer and attention model to perform language modeling. BERT allows for a better understanding of language context than two independent one-way spliced language models: GPT left-to-right single-item language pre-training and ELMo's autoregressive pre-training [7]. BERT trains models in an unsupervised manner with two clever approaches: Masked Language Modeling and Next Sentence Prediction. Without the time and manpower required to annotate data, these two methods can be used to obtain training data at a lower cost in an unsupervised manner. After the model is fitted, BERT can well predict the masked words and learns the inner logic of the text. The structure of the model is shown in Figure 4. BERT is a network model consisting of the stacked transformer encoder layer, supplemented by word encoding and location encoding. In the diagram, E_1, E_2, $\cdots$, E_m denote sequences of split-word text. Each word representation consists of word vector, segment vector and position vector. The special marker [CLS] is added to represent the start of a sentence, and [SEP] stands for the end of the sentence. Then feature extraction is carried out through bidirectional transformer encoder coding to get the vector representation of the text T_1, T_2, $\cdots$, T_m.

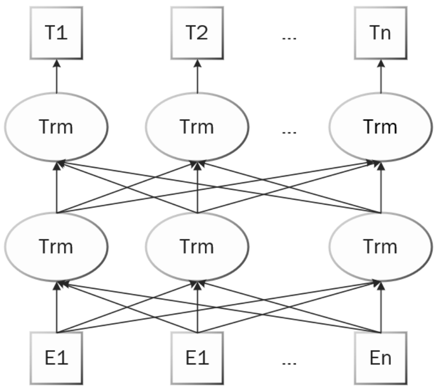

Figure 4. *Structure of BERT model.*

In the BERT model, the encoder part of the transformer model is responsible for mapping the computation of natural language sequences into a mathematical representation of the hidden layer, the model structure of which is shown in Figure 5.

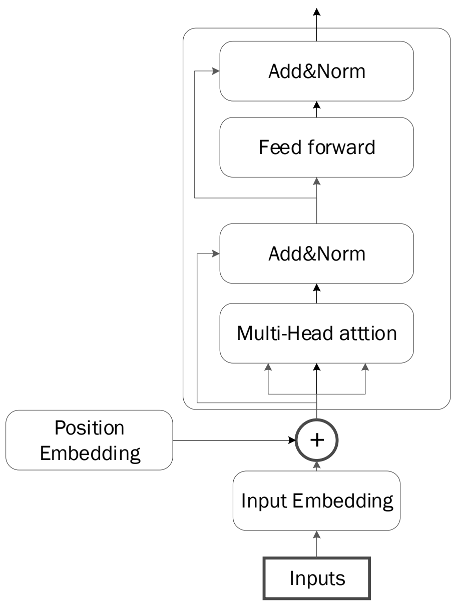

Figure 5. *Structure of Transformer Encoder.*

The transformer model [8] lacks the iterative operations of a recurrent neural network and does not recognize sequential relationships in language, so the transformer adds positional coding to learn the dependencies between positions and the temporal properties of natural language and superimposes them on the input vector.

The self-attention mechanism is a key part of Transformer. The main idea is to calculate the correlation between the current word and other words in a sentence and to assign higher weights to key features by updating the weight coefficient matrix. This is implemented by assigning three weight parameters W_Q, W_K and W_V to the input vector $X_{Embedding}$. After linear projection, the Q, K and V matrices are obtained, and the self-attention score is calculated using the following formula:

$$Q = X_{Embedding}W_Q \tag{1}$$

$$K = X_{Embedding}W_K \tag{2}$$

$$V = X_{Embedding}W_V \tag{3}$$

$$Attention(Q, K, V) = Softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

The self-attention matrix QK^T, denoting the correlation between words in the same sentence, is first found and normalized using softmax so that the sum of the attention weights of each word and all other words is 1. The attention matrix is then used to weight V to obtain a representation of the feature vector. The multi-headed attention mechanism, on the other hand, partitions $X_{Embedding}$ into H copies to compute self-attention separately, and finally output using the vector slicing. One set of linear variations extracts features in one dimension, whereas multiple sets allow more features to be extracted from higher dimensions. As a result, multiple semantic meanings are extracted.

Feedforward neural networks are essentially two fully-connected layers, which allow the gradient to be back-propagated directly to the initial layer by taking a shortcut. To accelerate convergence, Add & Norm is normalized to the standard normal distribution after adding the input and output from the previous layer.

2.2.2. BiLSTM-CRF Model

Bi - Long Short - Term Memory-Conditional Radom Field (BiLSTM-CRF) [9] was proposed for named entity recognition or sequence labeling. The effect is better than the simple CRF or BiLSTM.

Long Short-Term Memory (LSTM) is an improved model of the RNN model. Compared to RNN, LSTM can learn what information is memorized or forgotten during the training process due to its “forgotten gate” and “memory unit” design features and can better capture the longer distance dependencies in the examples. Bidirectional Long Short-Term Memory is a combination of forward LSTM and backward LSTM, the same input sequence is plugged into two separate LSTMs, and then the hidden layers of the two networks are connected together and plugged into the output layer for prediction, so it is good at handling long-term contextual information.

CRF [10] is a common sequence labeling algorithm that learns the constraint relations of adjacent labels from training samples, making the labeled sequences more scientific. It is described mathematically as shown in Equation 5, where the input observation sequence x is a sentence and the output state sequence y is an entity labeling sequence and given a conditional random field P(y|x), the optimal global solution is obtained by finding the output sequence y* with the maximum conditional probability.

$$y^* = argmaxP(y|x) \tag{5}$$

In the task of named entity recognition, BiLSTM is good at processing long-term context information. However, if there are strong dependencies between the output layers (for instance, B-PER labels should be followed by I-PER labels instead of I-LOC labels), BiLSTM cannot model the constraints, leading to illegal predicted label sequences. CRF can infer the conditional distribution of unknown labels using the labels predicted from the preceding text, so that the output sequence conforms to the constraints of basic dependencies. BiLSTM-CRF can make full use of the advantages of the above two models, take into account the dependencies between labels while focusing on contextual information, and ensure the validity of named entity recognition.

3. Models and Methods

3.1. Knowledge Fusion

Knowledge fusion [11-13] is an important method to provide more comprehensive knowledge sharing by aligning, correlating, and merging multiple related knowledge bases into an organic whole. Knowledge fusion allows for the addition of legal knowledge within the knowledge graph to provide support for caseworkers. Disciplinary Regulation of the Communist Party of China is the main basis for case characterization and discipline measurement. Through the analysis of this law and regulation, it is found that disciplinary act, disciplinary severity, and punishment can be extracted as entities from each article, and “belong to”, “contain”, and “give” are used as relationship categories to obtain the knowledge modeling of laws and regulations, as shown in Figure 6.

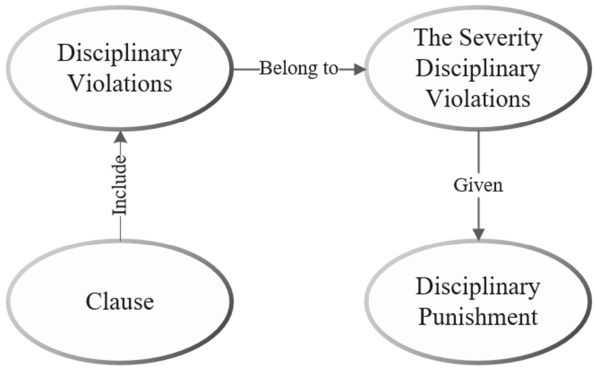

Figure 6. *Structure of legal and regulatory knowledge model.*

In this paper, the entities and relationships of the above design are extracted from unstructured shelf text data by manual as well as by keywords, etc. For each adjacent pair of entities, the corresponding relationship is added to form a triple "entity-relationship-entity" to form a knowledge base of laws and regulations.

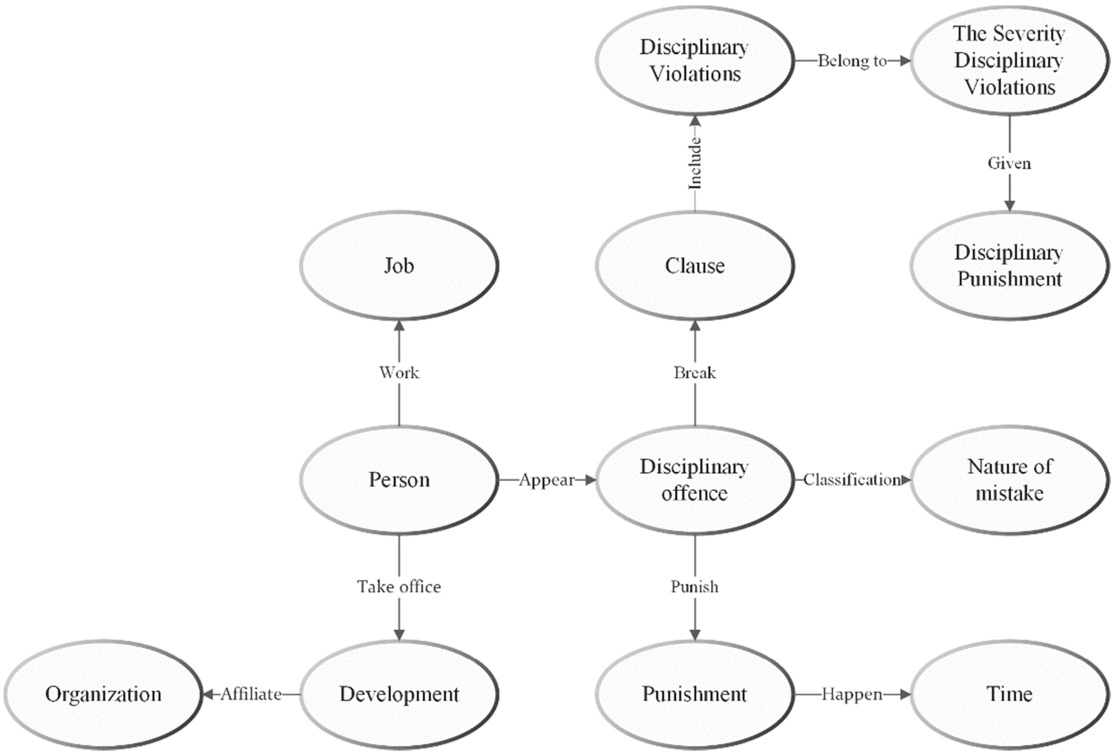

Figure 7. *Model structure of disciplinary supervision knowledge graph.*

Then, the law and regulation entities are associated with the disciplinary facts in the case knowledge graph, and the "Disciplinary offence-break-Clause" relationship is added to integrate into a complete discipline inspection and supervision knowledge graph. The knowledge model structure is shown in Figure 7.

In this paper, we calculate the similarity between the "Disciplinary offence" entity of the case knowledge map and the "Disciplinary violations" entity of laws and regulations to complete the knowledge fusion, and the accuracy is improved by manual error correction. If the similarity calculation threshold is greater than 0.8, the entities are judged to be of the same class. Then the "Disciplinary violations" entity corresponding to the "Article" entity is associated with the "Disciplinary offence "Disciplinary offence-break-Clause relationship" is created by associating the "article" entity corresponding to the "Disciplinary violations" entity with the "Disciplinary offence" entity. Thus, the knowledge fusion of multi-source data is realized, and a more comprehensive knowledge graph of discipline inspection and supervision is constructed. The final knowledge graph is shown in Figure 8.

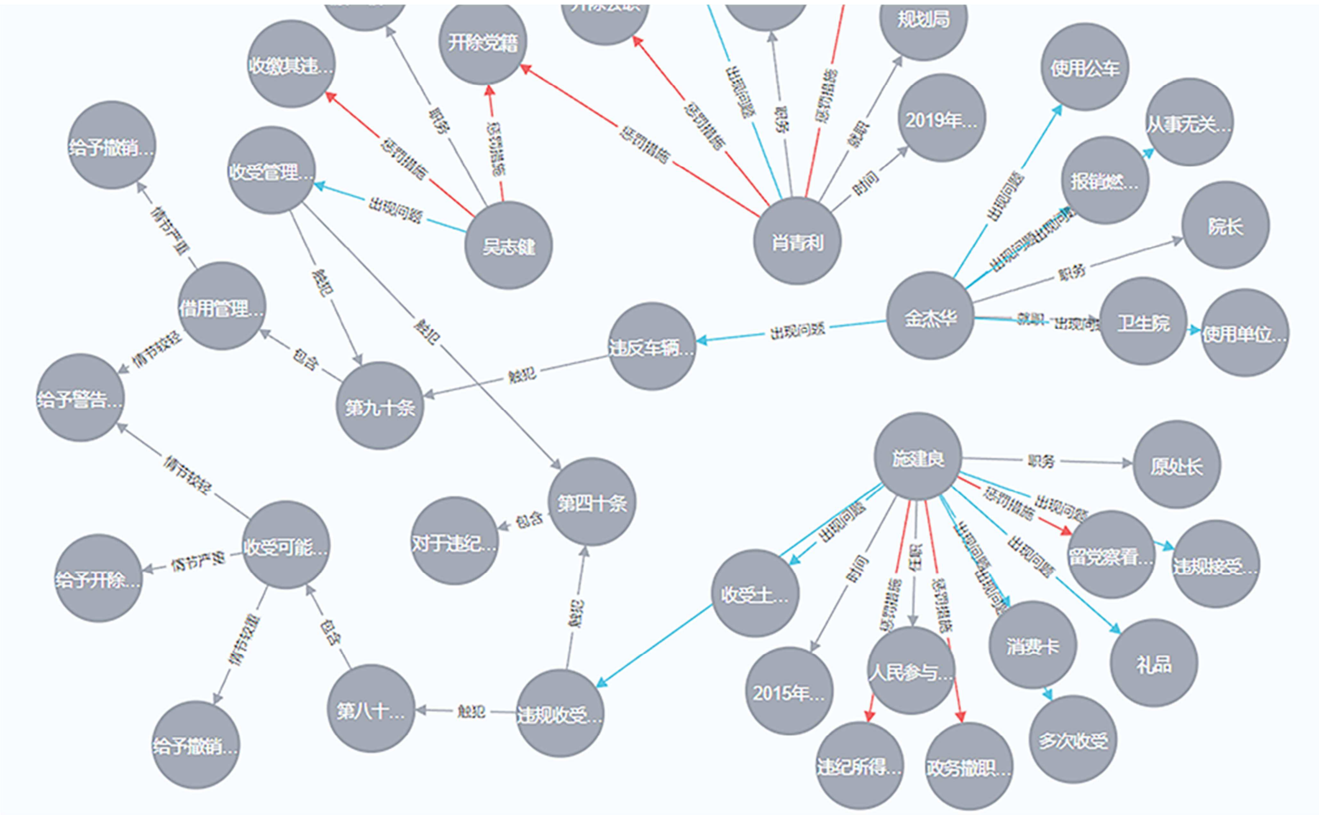

Figure 8. *Partial display of disciplinary supervision knowledge graph.*

3.2. Qualification of the Case

The characterization of a case literally means: to determine the nature of the case. It means that the judiciary determines the nature of the case according to the relevant legal provisions for a criminal act that has occurred. New cases are emerging, different cases qualitative and disciplinary standards are not uniform, and there are more disciplinary situations under the legal norms. Therefore, there is the problem that the nature of errors is easily confused. The typical cases and relevant regulations in the knowledge mapping of discipline inspection and supervision can assist in realizing intelligent case characterization and discipline measurement. The core of case characterization and discipline measurement based on the knowledge map of discipline inspection and supervision lies in the semantic understanding of case descriptions. On the one hand, disciplinary subjects, disciplinary acts and other disciplinary constitutive elements are the keys to case characterization. On the other hand, case descriptions are in the form of natural language, while they are in the form of structured triads in knowledge mapping, and they are not the same in semantic representation. Therefore, this paper uses named entity recognition technology to extract key elements from nascent case descriptions, perform entity alignment, and find out similar cases.

Named entity recognition [14-17], as a key technique for case characterization, is a fundamental task in natural language processing. Its purpose is to identify named entities such as person names, place names, and organization names in corpus. In order to improve the precision of extracting key elements of cases such as disciplinary subject and disciplinary offence, in this study, a hybrid model of BERT and BiLSTM-CRF was adopted. The structure is shown in Figure 9.

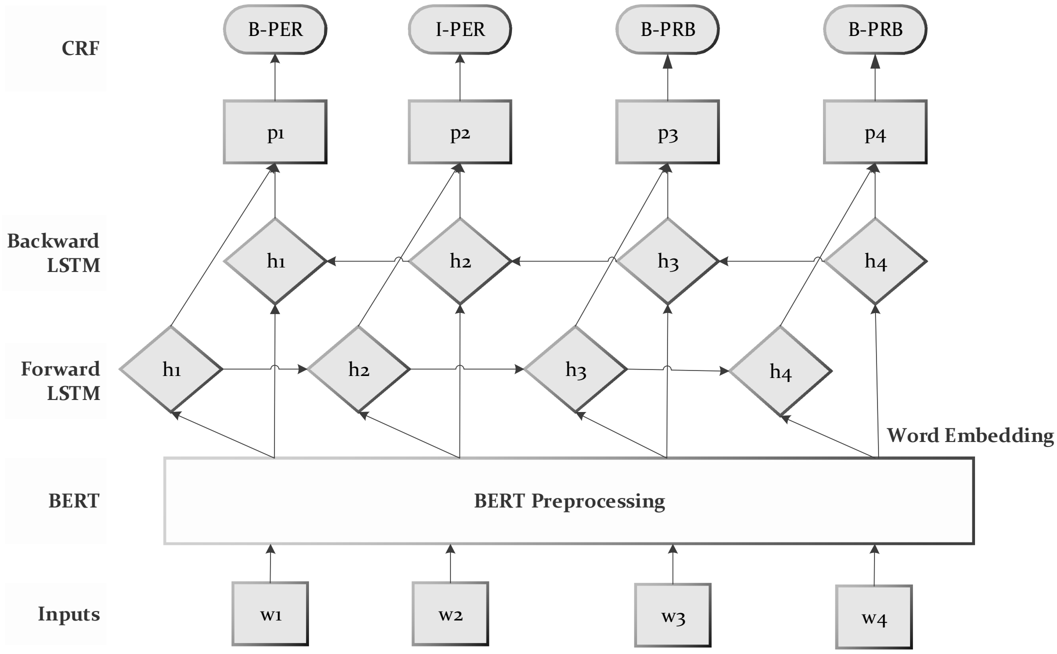

Figure 9. *Structure of NER model.*

In the first layer of the BERT model, words were randomly masked in the process of acquiring word vectors and then predicted at the position of the original words during pre-training to obtain contextual representations of the words. The second BiLSTM layer was used to automatically extract sentence features. Each word in a sentence was used as input for each time step of BiLSTM, the implicitly encoded representations of the character vectors were obtained by the forward LSTM and backward LSTM respectively, and then stitched together to obtain the implicit state representation at each position. In the third layer of CRF, the transfer probabilities between the labels were modelled. The final prediction was obtained by learning the order dependency information between the labels. In this study, BIO word labels were utilized to label all named entities (person name, position, department, disciplinary offence, compensatory behaviour, etc.). For instance, the first word of disciplinary offence was represented by B-PRB and the rest by I-PRB.

3.3. Case Measurement Disciplinary Judgment

Discipline measurement is to give appropriate punishment according to the severity of the violation, provided that a certain behaviour has constituted a disciplinary violation. Discipline measurement research based on the elements of the case can provide guiding cases and relevant regulations that can help achieve a balance of case discipline. But cases of the same type also need to be treated differently according to the disciplinary violations. The CPC disciplinary regulations also provide for the same disciplinary violation to be divided into different grades of punishment according to the severity of the circumstances. For example, in Article 88, if a person accepts gifts and gratuities that affect his official duties and the circumstances are less serious, he shall be given a warning or a serious warning within the Party. However, there is no uniform standard for the division and judgment of the severity of the circumstances, and the consideration of the severity of the circumstances is different for each case, which needs to be grasped slowly from practice. Through the analysis of typical cases of violation of party discipline and rules, there are no obvious keywords prompted in the case description, but they are reflected in the punishment results. Therefore, in this paper, the case quantity discipline is considered as a text classification task [18-20], and the severity of disciplinary circumstances of a large number of previous cases is learned by training the Bert model to predict the severity of circumstances of new cases. In the text classification task, using the judgment results in a large number of previous cases as the basis for classification labels, the Bert model learns the contextual semantic features of the case descriptions, uses the output vector corresponding to the sentence head label "[CLS]" as the semantic representation of the text, and calculates the cross-entropy between the classification labels and the true labels, and uses it as the optimization target. Finally, the normalization process is performed by softmax to output the classification of the degree of disciplinary circumstances for each case.

3.4. Results of Case Characterization and Discipline Measurement

The knowledge map of discipline inspection and supervision is modeled and designed based on cases and laws and regulations, with a clear structure and relationships. The general template of query statements can answer the question of case characterization and discipline measurement, and provide qualitative and discipline prediction for new violation facts based on previously occurred cases and laws.

4. Experiment and Analysis

4.1. Dataset Acquisition

In this paper, the typical cases of discipline violations reported in the supervision and exposure section of the website of the central and local commissions for Discipline Inspection are selected as the data source. This data source contains 10,031 texts of discipline violations, which are composed of three parts: nature of discipline violation, case description and punishment result. We divided these typical cases into the training set, validation set and test set in an 8:1:1 ratio. In addition, both named entity recognition and circumstance severity prediction steps need corresponding data sets, so data sets of these two parts need to be constructed.

First, the case description text is segmented into short sentences, and sequence-labeled with BIO tags to make a named entity recognition dataset.

Table 1. *BIO tag category.*

Label	Description
B-PER	The beginning of the disciplinary body
I-PER	The remainder of the disciplinary body
B-JOB	The beginning of job
I-JOB	The remainder of job
B-ORG	The beginning of organization
I-ORG	The remainder of organization
B-PRB	The beginning of the disciplinary violation
I-PRB	The remainder of the disciplinary violation

When constructing the prediction data set of the severity of disciplinary violations, manual labeling was carried out based on the rules formulated by field experts. Each case description corresponds to a category label, and the sample number of category labels is shown in Table 2. It can be seen that there is a serious problem of unbalanced data distribution in the data set. Under the premise of not affecting the experimental results, the undersampling of the majority of samples is adopted to achieve the balance between the minority samples and the majority samples, and the proportion of the three samples is adjusted to 1:1:1.

Table 2. *Category label samples.*

Category	Quantity
Minor Circumstance	1180
Serious Circumstance	132
Critical Circumstance	156

4.2. Experiment Environment and Evaluation Indicators

The experiments were written in python based on the Tensorflow platform. The CPU is intel Xeon Gold6139. The GPU is GTX 2080Ti with 11G memory.

For named entity recognition and text classification, common evaluation indicators include Precision, Recall and F1-score. Each evaluation indicator is calculated as follows:

$$Precision = \frac{TP}{TP+FP} \tag{6}$$

$$Recall = \frac{TP}{TP+FN} \tag{7}$$

$$F1 = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{8}$$

Where TP (True Positive) measures the extent to which the model correctly predicts the positive class; TN (True Negative) measures the extent to which the model correctly predicts the negative class; FP (False Positive) occurs when the model predicts that an instance belongs to a class that it actually does not; FN (False Negative) occurs when a model predicts an instance as negative when it is actually positive.

4.3. Model Performance Analysis

4.3.1. Named Entity Recognition Experiment

In this experiment, the Adam optimizer was used, with a learning rate of 0.001 and a maximum input text length of MAX_SEQ_LEN of 128. The BATCH_SIZE of the model training was 32, with 10 rounds of training. The dropout was set to 0.2 to prevent over-fitting. BiLSTM and BiLSTM-CRF models were used as comparison experiments, and the experimental results are shown in Table 3.

Table 3. *Comparison of named entity recognition model.*

Model	Accuracy	Recall	F1
BiLSTM	0.6908	0.6742	0.6862
BiLSTM-CRF	0.7212	0.7062	0.7127
BERT-BiLSTM-CRF	0.7334	0.7054	0.7260

The experimental comparison results show that the hybrid model has better experimental results than the single model. Firstly, BiLSTM improved the F1 score by 2.1% after adding the CRF module. This is mainly because CRF compensates for BiLSTM's inability to cope with correlations between labels (for instance, sequences like "O, I-PER" cannot be output) and improves the named recognition effect. Secondly, based on the BiLSTM-CRF, the BERT model was introduced to obtain dynamic word vectors, and the highest values of all the indicators were achieved in the experiments. The BERT model can fully extract character-level, word-level, sentence-level and even inter-sentence relationship features, so that the pre-trained word vectors can better characterize syntactic and semantic information in different contexts, enhance the generalization ability of the model and improve the performance of entity recognition. Experimental results show that this model can improve the recognition effect of named entity recognition.

4.3.2. Circumstance Severity Prediction

In this experiment, the hyper-parameters were learning rate 0.01, the maximum length of input text MAX_SEQ_LEN was 512, and BATCH_SIZE for model training was 32. A total of 10 rounds were trained. CNN, TextCNN, and BERT models were used as control experiments, and the model comparison results are shown in Table 4.

Table 4. *Comparison of circumstance severity prediction model.*

Model	Accuracy	Recall	F1
CNN	0.6671	0.6732	0.6801
TextCNN	0.6766	0.6542	0.6827
BERT	0.7258	0.7134	0.7308

According to the comparison of evaluation indicators of each model on the circumstance severity prediction datasets, the F1 score has been improved by 3.06% after further extracting deep semantic features with the BERT pre-training model, as compared to the classification effect of the TextCNN text convolution model. This demonstrates the BERT model shows a good effect on the circumstance severity prediction sub-task. However, due to the imbalance in the original data, the BERT model undersampled on most samples, and the reduced number of samples led to lower scores for each indicator.

5. Conclusion

In the field of discipline inspection and supervision, most of the previous studies on characterization and discipline measurement tasks have been conducted with the aid of knowledge retrieval, similar case recommendations, etc. However, fewer studies target case characterization and discipline measurement. Therefore, a method for case characterization and discipline measurement based on discipline inspection and supervision knowledge graph was proposed in this study. And the key case elements affecting the characterization and discipline measurement were extracted with the help of text classification and information extraction techniques, so as to implement the case characterization and discipline measurement using the knowledge graph as supplementary information. Afterwards, the entity extraction for named entity recognition using the Bert-BiLSTM-CRF hybrid model and the learning of circumstance severity of the case description using the pre-trained language model were proposed and experimentally validated, respectively. The results show that the proposed method is a useful exploration of case characterization and discipline measurement tasks, which provides an important reference for the application of knowledge graph in the field of discipline inspection and supervision.

Acknowledgements

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