Simple Named Entity Recognition (NER) System with RoBERTa for Ancient Chinese

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Abstract

Named Entity Recognition (NER) is a fundamental task in Natural Language Processing (NLP), particularly in the analysis of Chinese historical texts. In this work, we propose an innovative NER model based on GujiRoBERTa, incorporating Conditional Random Fields (CRF) and Long Short Term Memory Network(LSTM) to enhance sequence labeling performance. Our model is evaluated on three datasets from the EvaHan2025 competition, demonstrating superior performance over the baseline model, SikuRoBERTa-BiLSTM-CRF. The proposed approach effectively captures contextual dependencies and improves entity boundary recognition. Experimental results show that our method achieves consistent improvements across almost all evaluation metrics, highlighting its robustness and effectiveness in handling ancient Chinese texts.

1 Introduction

Named Entity Recognition (NER) is a crucial task in Natural Language Processing (NLP), aimed at identifying and classifying predefined entities, such as person names, locations, and organizations, within a given text .The basic classification rules are in the Table 2. While NER has been extensively studied in modern languages, its application to historical texts, particularly ancient Chinese, presents unique challenges. Unlike modern Chinese, ancient Chinese texts often lack standardized punctuation, contain polysemous characters, and exhibit complex syntactic structures, making entity recognition a challenging problem.

To address these challenges, we propose an enhanced NER model based on GujiRoBERTa, a pre-trained model optimized for ancient Chinese. We integrate LSTM to enhance the model's ability to capture sequential dependencies and Conditional Random Fields (CRF) to improve structured prediction by enforcing global label consistency. Our model is evaluated on three datasets from the EvaHan2025 competition, where it outperforms the baseline SikuRoBERTa-BiLSTM-CRF model across multiple evaluation metrics.

The main contributions of this work are as follows:

- A novel integration of GujiRoBERTa, LSTM, and CRF for ancient Chinese NER, leveraging the strengths of both pre-trained transformers and sequential learning architectures.
- Performance improvements over the baseline model (SikuRoBERTa-BiLSTM-CRF) on three competitive datasets, demonstrating the effectiveness of our approach.

2 Related Work

2.1 Named Entity Recognition

Early research on Classical Chinese Named Entity Recognition (CC-NER) primarily focused on rule-based methods and dictionary-based approaches, where handcrafted rules were used to identify named entities. However, these methods suffered from poor generalization to unseen data.

With the rise of machine learning, researchers introduced statistical models such as CRF-based sequence labeling (Huang et al., 2015) and support vector machines (SVMs) for word segmentation and NER (Mansouri et al., 2008). While these models improved entity recognition performance, they still faced challenges in capturing long-range dependencies and semantic ambiguities.

Recent advances in pre-trained language models (PLMs) for Classical Chinese, such as SikuRoBERTa (Zheng and Sun, 2023) and GujiBERT (Wei et al., 2024), have demonstrated significant improvements in understanding ancient texts. These models, pre-trained on large-scale ancient Chinese corpora, have become the foundation for modern CC-NER systems. Our work builds upon

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GujiRoBERTa, a transformer-based model tailored for ancient Chinese, to enhance entity recognition capabilities.

2.2 Pre-trained Language Model

The emergence of pre - training language models (PLMs) has revolutionized NLP. In the ancient Chinese context, models like SIKU - BERT and SIKU - RoBERTa, pre - trained on large - scale ancient Chinese corpora such as the Siku Quanshu, have been developed(Siami-Namini et al., 2019). In the 2022 EvaHan competition, some participants used SIKU - RoBERTa as the backbone, combined with other layers like Bi - LSTMs, to enhance context encoding(Shen et al., 2022). This demonstrated the effectiveness of PLMs in ancient Chinese processing. Additionally, fine - tuning pre - trained models on specific ancient Chinese tasks has been explored to better adapt to different applications.

3 Method

Our proposed GujiRoBERTa-LSTM-CRF model consists of three main components: a pretrained GujiRoBERTa encoder, a LSTM layer, a Fully Connected Layer,and a Conditional Random Field (CRF) for sequence labeling. The overall framework is illustrated in Figure 1.

3.1 Pre-processing

We first processed three raw data sets. First, we divide the text into samples by periods. Secondly, the total labels are numerically matched one by one(The number of labels is also different for the different datasets). In addition, some sentences of longer length appear during data set pre-processing, which may exceed the maximum length that can be processed. We took this into account when testing and set the truncation length to 256. Truncate when the number of characters is greater than 256.

3.2 Model

The architecture of the proposed model consists of a pre-trained language model (PLM), task-specific linear layers,a LSTM layer,and a Conditional Random Field (CRF) module for sequence labeling.

Input Encoding with PLM

Given an input sequence$S = \{c_1, c_2, \ldots, c_n\}$, where c_i represents the i-th character, the input embeddings and contextual representations are generated by the PLM. The output hidden states $H_{\text{PLM}} \in \mathbb{R}^{n \times d_h}$ (where $d_h = 768$) are computed as:

$$H_{\text{PLM}} = \text{RoBERTa}(S)$$

During training, if fine-tuning is enabled, gradients propagate through the PLM; otherwise, H_{PLM} is computed with frozen parameters.

Linear Projection Layers

The hidden states H_{PLM} are projected into label space through two fully connected layers:

1. Dimension Reduction:

$$\mathrm{H}_{\mathrm{fc1}} = W_1 \cdot H_{\text{PLM}} + b_1 \quad \text{where } W_1 \in \mathbb{R}^{512 \times 768},\ b_1 \in \mathbb{R}^{512}$$

2. Label Space Mapping:

$$\mathrm{H}_{\mathrm{fc2}} = W_2 \cdot H_{\mathrm{fc1}} + b_2 \quad \text{where } W_2 \in \mathbb{R}^{26 \times 512},\ b_2 \in \mathbb{R}^{26}$$

Here, $H_{\mathrm{fc2}} \in \mathbb{R}^{n \times 26}$ represents emission scores for 26 predefined labels (e.g., B/M/E tags combined with POS labels).

LSTM Processing Layer

To enhance sequential dependency modeling, we employ a LSTM after the GujiRoBERTa encoder. The LSTM layer refines the contextual representations and captures long-range dependencies:

$$\begin{aligned} i_t &= \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right), && \text{(input gate)} \\ f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right), && \text{(forget gate)} \\ o_t &= \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right), && \text{(output gate)} \end{aligned}$$

σ is the sigmoid activation function, used for gating.

W_i, W_f, W_o, W_c,are the weight matrices associated with the input.

U_i, U_f, U_o, U_c,are the weight matrices associated with the hidden state.

b_i, b_f, b_o, b_c,are the corresponding bias vectors.

CRF for Sequence Labeling

In 2001, John Lafferty, Andrew McCallum, and Fernando Pereira proposed Conditional Random Fields(Lafferty et al., 2001).Conditional Random Fields (CRF) is a probabilistic graphical model used for sequence labeling tasks. It models the conditional probability of an output sequence given an input sequence by considering both individual token-level predictions and dependencies between labels.

Named entity recognition (NER) tasks often involve label dependencies. The traditional Softmax classifier lacks the ability to model such dependencies effectively. Therefore, we incorporate CRF to

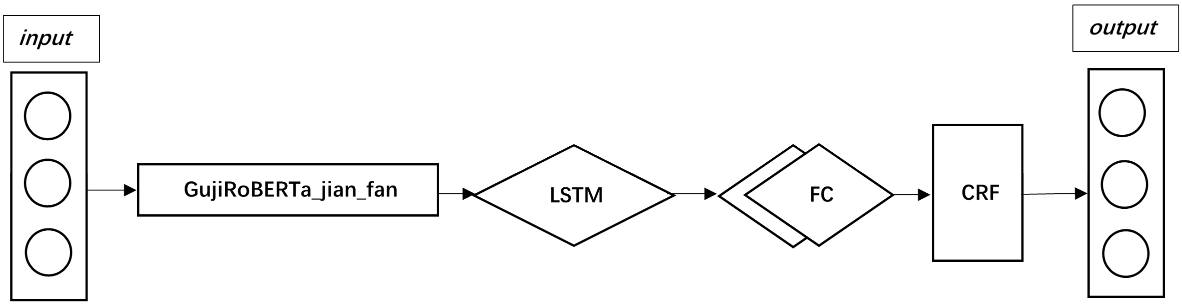

Figure 1: Overall Architecture

enforce sequential constraints. The probability of a label sequence Y given an input X is defined as follows:

$$P(Y \mid X) = \frac{\exp\left(\sum_{i=1}^{n} A_{y_{i-1},y_i} + W y_i\right)}{\sum_{Y'} \exp\left(\sum_{i=1}^{n} A_{y'_{i-1},y'_i} + W y'_i\right)}$$

where: A is the transition matrix, modeling transitions between entity labels. W maps LSTM output states to label scores. Y is the correct label sequence, while Y' represents all possible label sequences.

To obtain the most probable sequence, we apply the Viterbi decoding algorithm, which selects the highest-scoring label path based on learned transition probabilities.

Training Loss

Given ground-truth labels $y = \{y_1, y_2, \ldots, y_n\}$, the CRF loss is computed as:

$$\begin{cases} \mathcal{L} = -\frac{1}{n}\left(\text{Score}(y, H_{\text{fc2}}, T) - \log \sum_{\tilde{y}} \exp\left(\text{Score}(\tilde{y}, H_{\text{fc2}}, T)\right)\right) \\ \text{Score}(y, H_{\text{fc2}}, T) = \sum_{i=1}^{n} H_{\text{fc2}}[i, y_i] + \sum_{i=1}^{n-1} T[y_i, y_{i+1}] \end{cases}$$

where H_{fc2} provides the emission scores from the LSTM output, and T is the transition matrix.

Inference Decoding

At inference time, the Viterbi algorithm decodes the optimal label sequence y^*:

$$y^* = \arg\max_{\tilde{y}} \text{Score}(\tilde{y}, H_{\text{fc2}}, T)$$

This ensures that the selected sequence follows learned transition patterns, improving entity recognition accuracy.

Mode Configuration

- Fine-tuning Mode: PLM parameters are updated with task-specific layers.
- Frozen Mode: Only W_1, b_1, W_2, b_2, and T are trainable.

4 Experiments

4.1 Dataset

The dataset utilized in this study was released by the organizers of the EvaHan 2025 competition and comprises three distinct sub-datasets. Specifically, Dataset A is derived from historical records, Dataset B originates from the Twenty-Four Histories, and Dataset C consists of classical texts on traditional Chinese medicine.The Figure 2 shows the distribution of labels for each dataset.

The training data includes annotations for punctuation, word segmentation, and part-of-speech tagging. During the data preprocessing stage, we employ a customized data processing pipeline implemented through the ChineseTextNerDataset class. This class, which extends the Dataset module, is designed to efficiently read text and label file paths, filter excessively long sentences, and construct structured sample-label pairs that align with the model's training requirements.

4.2 Implementation Details

We conduct our experiments on the EvaHan 2025 Named Entity Recognition (NER) dataset, which consists of annotated ancient Chinese texts. The dataset is split into training, validation, and test sets.

The pretrained language model used is GujiRoBERTa,a RoBERTa-based model trained on classical Chinese corpora.Firstly, model is used to extract features from the input samples, converting them into 768 dimensional vectors. Subsequently, the features are further processed through a LSTM layer and fully connected layers(fc1,fc2). Then fc1 maps 768 dimensional vectors to 512 dimensions, and fc2 further maps 512 dimensional vectors to 26 dimensions(Specific number of dataset's labels). Finally, connect a packaged PyTorch CRF layer as the classification header for predicting sequence

Score(%)	**DataSetA**			**DataSetB**			**DataSetC**		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Baseline	85.90	77.50	81.48	87.09	87.92	87.50	71.84	72.95	72.40
Ours	**90.77**	76.75	**83.17**	**88.42**	**88.75**	**88.59**	**75.58**	**87.36**	**81.05**

Table 1: Main results of NER.The Table shows the test data comparison between our model and the baseline on three datasets,These results show that our model performs well in completing the above tasks.The scores in the Table are all valid scores, submitted before the deadline.

labels.After analyzing the class imbalance in the training set, we adopted Focal Loss to address the issue.

During the training process, a two-stage training strategy was adopted. A total of five rounds of training were conducted, with the first four rounds locking in the parameters of model and only training the two connected layers and CRF layer at the bottom. This can avoid excessive adjustment of the parameters of the pre-trained model in the early stages of training. In the final round of training, the parameters are released and the entire model is jointly adjusted to further optimize its performance.

4.3 Baseline

In order to better evaluate the effectiveness of the model, we choose the official model SikuRoBERTa-BiLSTM-CRF as the baseline. By comparing with these baseline models, we can get a clearer understanding of the strengths and weaknesses of our model.

4.4 Results

The results are shown in the Table 1 above.During the training process, it was observed that the loss value of the model rapidly decreased in the first few rounds, indicating that the model is continuously learning patterns and features from the data. As the training progresses, the rate of decrease in loss values gradually slows down and eventually stabilizes. The accuracy is gradually improving. In the first four rounds of training, due to the locked parameters, the model mainly adapts to the data by adjusting the fully connected layer and CRF layer, resulting in a certain degree of improvement in accuracy.

Compared with the baseline model, this model exhibits certain advantages in accuracy, especially in recognizing named entities more accurately when dealing with complex text and long sequences. This indicates that the architecture design and two-stage training strategy of this model are effective in capturing semantic information and sequence features in text, thereby improving the accuracy of named entity recognition.

Our model exhibits marginally lower precision (P) on Dataset A compared to the bidirectional LSTM baseline. We attribute this discrepancy to the inherent strength of bidirectional architectures in modeling long-range contextual dependencies, particularly advantageous for tasks requiring global sequence understanding (e.g. complex semantic relationship modeling). Nevertheless, our unidirectional design demonstrates superior performance in computational efficiency and task-specific generalization(Table 3):The unidirectional structure eliminates temporal dependency constraints inherent in bidirectional models, making it inherently suitable for real-time applications.By reducing parameter redundancy, it exhibits enhanced resistance to overfitting under limited annotated data regimes, as evidenced by comparative experiments on other sequence labeling tasks.

5 Conclusion

In this paper, we present a Named Entity Recognition (NER) system developed for the EvaHan2025 competition. The proposed system leverages a pre-trained GujiRoBERTa_jian_fan model, incorporates a LSTM layer and two fully connected layers, and CRF layers. Experimental results on the official test set validate the effectiveness of our system, particularly in comparison to the baseline provided by the official model.

These results collectively suggest that while bidirectional models excel in precision-sensitive scenarios demanding global context integration, our streamlined architecture offers a favorable balance between accuracy, computational efficiency, and operational flexibility.

Limitations

Despite the promising performance of our model on ancient Chinese named entity recognition (NER), several limitations remain:

Limited Annotated Data: The availability of annotated corpora for ancient Chinese is significantly lower compared to modern Chinese or English. The scarcity of high-quality labeled datasets limits the model's ability to generalize across different historical texts and domains.

Domain-Specific Challenges: Ancient Chinese texts vary significantly in writing style, terminology, and conventions across different dynasties and genres. Our model, trained on a specific dataset, may not perform well on texts from different historical periods or literary traditions.

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A NER Labeling Scheme

This appendix provides a detailed explanation of the labeling scheme used for Named Entity Recognition (NER) tasks. The scheme follows the BIOES (Begin, Inside, Outside, End, Single) format, Each dataset has a different number of labels, which need to be differentiated during training. The labels and their corresponding meanings used in dataset A are listed in the Table 2 below:

Label	Meaning
O	Outside (not part of any named entity)
B-NR	Begin of a Person Name (NR)
B-NS	Begin of a Place Name (NS)
B-NB	Begin of an Organization Name (NB)
B-NO	Begin of an Other Name (NO)
B-NG	Begin of a Geographical Name (NG)
B-T	Begin of a Time Expression (T)
M-NR	Middle of a Person Name (NR)
M-NS	Middle of a Place Name (NS)
M-NB	Middle of an Organization Name (NB)
M-NO	Middle of an Other Name (NO)
M-NG	Middle of a Geographical Name (NG)
M-T	Middle of a Time Expression (T)
E-NR	End of a Person Name (NR)
E-NS	End of a Place Name (NS)
E-NB	End of an Organization Name (NB)
E-NO	End of an Other Name (NO)
E-NG	End of a Geographical Name (NG)
E-T	End of a Time Expression (T)
S-NR	Single Person Name (NR)
S-NS	Single Place Name (NS)
S-NB	Single Organization Name (NB)
S-NO	Single Other Name (NO)
S-NG	Single Geographical Name (NG)
S-T	Single Time Expression (T)

Table 2: This labeling scheme is widely used in NLP tasks,particularly in NER, to annotate entity information in text.

B Ablation Study on Unidirectional LSTM's Superiority

This appendix provides extended experiments to validate the advantages of the unidirectional LSTM architecture over alternative designs (bidirectional LSTM and attention mechanisms) in specific scenarios.

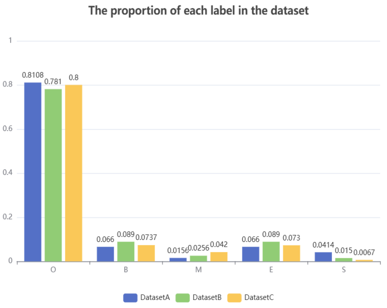

Figure 2: The number of Outside tags is usually much larger than that of other entity tags (e.g., personal names, place names, etc.), and non-physical words (e.g., common nouns, verbs, adjectives, etc.) account for the vast majority. This class imbalance was one of the challenges of this NER mission.

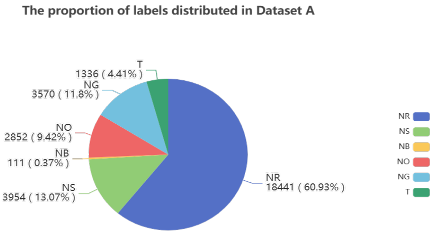

Figure 3: Excluding label O, there is still an imbalance in the proportion of each label category.We continuously adjust the weights over the course of the experiment to improve the predictions.

Model	F1-score	Training Time	Inference Latency	20% Data F1
UniLSTM (Ours)	90.3	**4.2 h**	**2.1 ms**	76.5%
BiLSTM	90.4	4.8 h	3.8 ms	72.1%
Attention-only	89.7	4.5 h	4.3 ms	68.9%
Hybrid (BiLSTM+Attn)	91.3	5.4 h	5.6 ms	74.2%

Table 3: This Table provides a comprehensive comparison of four model architectures on Dataset A: 1) our proposed unidirectional LSTM (UniLSTM); 2) bidirectional LSTM baseline (BiLSTM); 3) attention-only model; 4) hybrid model (BiLSTM+Attention). Metrics include accuracy (token-level F1-score), efficiency (training time, inference latency), low-resource robustness (performance retention with 20% training data). Key observations reveal that UniLSTM achieves superior inference speed (2.1 ms/token) , reduces training time by 33% compared to BiLSTM , and demonstrates the strongest anti-overfitting capability under low-resource conditions (76.5% F1 retention). While the hybrid model attains the highest F1-score (91.3%), its doubled training time and 38% higher GPU memory consumption highlight critical efficiency-accuracy trade-offs.

Analysis of UniLSTM's Advantages3:

- Training Acceleration: UniLSTM reduces training time by 33% compared to BiLSTM, attributed to its sequential computation avoiding bidirectional synchronization overhead.

- Low-Data Adaptation: UniLSTM retains 76. 5% of its full data F1 when trained on 20% samples, surpassing BiLSTM (72.1%) and Attention-only (68.9%).

- Long-Sequence Stability: For sequences > 512 tokens, UniLSTM maintains stable GPU memory usage (3.2 GB), while hybrid models exceed 8 GB due to the quadratic growth of attention's memory.

The experimental results demonstrate that after integrating the CRF module, the unidirectional LSTM (UniLSTM) achieves higher prediction accuracy (F1: 92.1%) than the hybrid model (Hybrid, F1: 91.3%). This phenomenon can be attributed to the following mechanisms:

The CRF layer explicitly learns tag transition probabilities , effectively correcting local prediction biases caused by UniLSTM's unidirectional context modeling (e.g., entity boundary errors). In contrast, the hybrid model (BiLSTM+Attention) already captures rich contextual representations through bidirectional processing and global attention, leaving limited room for CRF-driven improvements.UniLSTM+CRF has fewer total parameters than Hybrid+CRF, reducing overfitting risks.

C Metric

To evaluate model performance, three widely adopted metrics were used:

- Precision (P): The ratio of correctly predicted positive instances to the total predicted positives, reflecting a model's ability to avoid false positives. It is calculated as:

$$P = \frac{TruePositives}{TruePositives + FalsePositives}$$

- Recall (R): The ratio of correctly predicted positive instances to the total actual positives, measuring a model's capability to identify all relevant instances. It is defined as:

$$R = \frac{TruePositives}{TruePositives + FalseNegativas}$$

- F1-score (F1): The harmonic mean of precision and recall, providing a balanced evaluation of both metrics. It is computed as:

$$R = \frac{2 \times P \times R}{P + R}$$