A Joint Framework for Ancient Chinese WS and POS Tagging based on Adversarial Ensemble Learning

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Abstract

Ancient Chinese word segmentation and part-of-speech tagging tasks are crucial to facilitate the study of ancient Chinese and the dissemination of traditional Chinese culture. Current methods face problems such as lack of large-scale labeled data, individual task error propagation, and lack of robustness and generalization of models. Therefore, we propose a joint framework for ancient Chinese WS and POS tagging based on adversarial ensemble learning, called AENet. On the basis of pre-training and fine-tuning, AENet uses a joint tagging approach of WS and POS tagging and treats it as a joint sequence tagging task. Meanwhile, AENet incorporates adversarial training and ensemble learning, which effectively improves the model recognition efficiency while enhancing the robustness and generalization of the model. Our experiments demonstrate that AENet improves the F1 score of word segmentation by 4.48% and the score of part-of-speech tagging by 2.29% on test dataset compared with the baseline, which shows high performance and strong generalization.

Keywords: Adversarial Ensemble Learning, Word Segmentation, POS Tagging

1. Introduction

Recently, researchers have gradually paid more attention to traditional culture, and the understanding and study of ancient Chinese is an important part. However, there are many obstacles in understanding ancient Chinese due to the features of the separation of language and text, archaic and incomprehensible, and unclear segmentation. In order to better help researchers understand ancient Chinese and promote the inheritance of Chinese traditional culture, applying some basic tasks of natural language processing (NLP), such as word segmentation (WS), part-of-speech (POS) tagging, and named entity recognition (NER), to ancient Chinese has become an urgent need.

Chinese word segmentation, refers to the partitioning of a sequence of consecutive words in units of words into word-based sequences by word segmentation algorithms with the help of computer technology. Part-of-speech tagging refers to tagging the words in a sentence by part-of-speech tagging algorithms, that is, predicting the lexicality of words. These two tasks are the basis of many downstream tasks of natural language processing and play an indispensable role in various fields.

In fact, both the WS and POS tagging tasks can generally be regarded as sequence labeling tasks. Defining a suitable labeling scheme provides ideas to solve these problems. Due to the large differences between ancient Chinese and modern texts, the difficulty of understanding and the lack of obvious segmentation symbols, early ancient Chinese WS and POS tagging tasks would often be solved by taking a manual construction approach. These methods tend to have a high accuracy rate, with unacceptable cost. After that, methods based on lexical, dictionaries, and manual rules emerged. Researchers find strings that match those rules with the help of priority rules constructed manually by experts in various fields. However, these methods rely on the construction of dictionaries and knowledge bases, and system constructed tend to be less portable and scalable, and probably require experts in specific domain to spend a lot of time on construction and maintenance.

With the development of computer technology, the demand for automatic WS and POS tagging of ancient Chinese has increased, and algorithms based on machine learning and deep learning have emerged. Conditional Random Fields (CRF), Support Vector machines (SVM), Hidden Markov Models (HMM), Maximum Entropy Models (MEM), Long Short-Term Memory Networks (LSTM), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN) and so on are widely used in WS and POS tagging task of ancient Chinese. However, supervised learning methods above usually require large-scale labeled datasets, and the field of ancient Chinese often faces the problem of sparse labeled data. Therefore, pre-trained language models (PLM) with fine-tuning have come into the forefront of researchers’ attention. This approach essentially uses transfer learning to train a word vector model with rich semantic information using a large amount of unlabeled text, and then fine-tune it using labeled data, which can well solve the problem of lacking high-quality, large-scale labeled data in a specific domain.

However, WS and POS tagging models in modern standard Chinese often do not work well for ancient Chinese, and the trained models are often sensitive to noisy data and do not have good portability and transferability. Adversarial training (AT) and ensemble learning (EL) can help us solve these problems well. Adversarial training is an important way to enhance the robustness of neural networks. The essential idea of AT is adding some small but potentially misclassifying perturbations to the samples during training process will make the model adapt to such changes and thus be robust to the adversarial samples. Ensemble learning, on the other hand, as a common approach for supervised machine learning tasks, aims to improve the prediction results by the integration of multiple learning algorithms. Combining adversarial training with ensemble learning can enhance the portability and robustness of the model while improving the accuracy of ancient Chinese WS and POS tagging tasks.

In summary, we propose a joint framework based on adversarial ensemble learning for ancient Chinese WS and POS tagging tasks, called AENet, to address the problems of lack of large-scale annotation data, low model portability and robustness for joint tasks of ancient Chinese WS and POS tagging. The main innovations of this paper are as follows.
• We propose a joint framework for ancient Chinese 
  WS and POS tagging to reduce the noise caused 
  by individual task training process and improve 
  recognition efficiency of the model, with the idea 
  of pre-training and fine-tuning.
• We incorporate the ideas of adversarial training 
  and ensemble learning into the joint framework 
  to improve the robustness and generalization of our 
  model effectively.
• Compared with baseline, the proposed framework 
  achieves better performance on two ancient 
  Chinese datasets provided.

2. Related Work

With the deepening on ancient Chinese mining research, 
researchers are in full swing on the study of ancient Chinese 
WS and POS tagging tasks. For example, Yu et al. (2020) 
proposed an automatic WS model for ancient Chinese 
based on a nonparametric Bayesian model and deep 
learning. This method adopts an unsupervised multi-stage 
iterative training, aiming to mine valuable ancient Chinese 
WS models by jointly using Bayesian model and BERT, 
and training them repeatedly in large-scale unlabeled data. 
Cheng et al. (2020) designed an ancient Chinese WS and 
POS tagging model based on BiLSTM-CRF model, and by 
designing appropriate WS and POS labels, these two tasks 
were fused, which is similar to the method of task fusion in 
this paper. Stoeckel et al. (2020) proposed an ensemble 
classifier, namely LSTMVote, for the POS tagging task of 
Latin languages, which integrates multiple pre-trained 
classifiers to obtain the optimal model.

To solve the problem of lack of ancient Chinese annotated 
corpus, pre-trained language models have been introduced 
to the study. Based on the ancient literature corpus of 
Daizhige 1, GuwenBERT 2 model was proposed. This 
method combines the weight of modern Chinese RoBERTa 
model and a large number of ancient Chinese corpus on the 
basis of the continuation training technique, and transfers 
some linguistic features of modern Chinese to ancient 
Chinese, which substantially improves the performance of 
the model. After that, Wang et al. (2021) constructed 
SikuBERT and SikuRoBERTa pre-trained language 
models for ancient Chinese intelligent processing tasks 
based on the BERT, using the calibrated high-quality full-
text corpus of Siku Quanshu as an unsupervised training 
set, which provided support for researchers in ancient 
Chinese.

Numerous studies have proved that adversarial training can 
effectively improve the robustness and generalization of 
language models. FGSM and FGM adversarial training 
methods (Goodfellow et al., 2014; Miyato et al., 2017) 
were proposed, the core idea of which is to let the direction 
of perturbation follow the direction of gradient boosting. In 
these methods, authors assume that the loss function is 
linear or locally linear, and therefore the direction of 
gradient boosting is the optimal direction. The difference 
between FGSM and FGM is the normalization method, 
with FGSM taking max normalization of the gradient 
through the sign function and FGM using L2 normalization. In order to solve the linear assumption 
problem in FGSM and FGM, Projected Gradient Descent 
method (PGD) (Madry et al., 2017) was proposed, which 
can be used to solve the internal maximum problem. The 
core idea of PGD is to reach the optimum by multiple 
iterations and each iteration will project the perturbation to 
the specified range. However, this method can only utilize 
the gradient of the parameters and the gradient of the input 
alone. In order to utilize two gradients simultaneously and 
efficiently, FreeLB (Zhu et al., 2019) was proposed, which 
makes use of the gradient accumulated from multiple 
iterations to make updates and estimate the gradient more 
accurately.

Meanwhile, as an effective way of supervised learning, 
ensemble learning can obtain better prediction performance 
than using any individual learning algorithm alone by 
integrating multiple learning algorithms. At present, 
ensemble learning algorithms are mainly classified into 
three categories: Bagging, Boosting and Stacking, which 
correspond to parallel training, serial training and 
hierarchical training, respectively. With the help of the idea 
of ensemble learning, Izmailov et al. (2018) proposed a 
stochastic weight averaging (SWA) algorithm, whose core 
idea is that the average of multiple weights in the training 
process of a single model is closer to the optimal solution. 
A lot of practices have proved that SWA is superior to other 
optimization algorithms, such as SGD.

3. Model

In this section, we first introduce the task definition, and 
then present the overall framework of the joint model for 
ancient Chinese WS and POS tagging tasks. After that, we 
detail how to jointly use adversarial training and ensemble 
learning to improve model performance.

3.1 Task Definition

Given an input sentence of ancient Chinese with n tokens 
X = \{x_1, x_2, ..., x_n\}, the target sentence can be \( Y = \{y_1, y_2, ..., y_n\} \), 
where \( y_i = w_s y_i - p_{ox_i} \), for example, \( y_1 = B - N_R \). In the 
formula above, \( w_s \) = \{B, I, E, S\}, \( B \) means the current token 
is the beginning of a multi-token word, \( I \) means the current 
token is in the middle of a multi-token word, \( E \) means the 
current token is the end of a multi-token word, and \( S \) means 
the current token is a single word. Through this tagging 
method, the task of WS for ancient Chinese can be solved 
automatically. And then, \( p_{ox} = \{A, C, D, J, M, N, NR, NS, ...\} \), 
which refers to common parts of speech in texts. The task 
in this paper can be defined in the form of Equation 1, that 
is, given a sequence \( X \), find the optimal sequence \( Y \) 
that maximizes the probability of \( p(Y | X) \). According to the 
above tagging methods, the joint task of WS and POS 
tagging of ancient Chinese can be realized easily, thus 
reducing the noise impact and error propagation that may 
be brought by separate task training.

\[
Y' = \arg \max p(Y | X)
\] (1)

3.2 Model Framework

The overall joint framework for ancient Chinese WS and 
POS tagging based on adversarial ensemble learning, that 
is, AENet, is shown in Figure 1. The overall framework of 
AENet is carried out with the idea of pre-training and fine-

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1 http://www.daizhige.org/
2 https://github.com/ethan-yt/guwenbert
tuning. Namely, given an ancient Chinese sequence, it is cut into token sequences firstly. Then, the token sequence is input into the pre-trained language model for fine-tuning, and word embeddings with rich semantic information can be obtained. The final predicted label sequences are obtained by feeding word embeddings into the CRF layer. The specific process is shown in Equation 2.

\[
\text{Embedding} = \text{PLM}(X) \\
Y = \text{CRF}(\text{Embedding}) \\
\text{Loss} = -\log P(Y | X)
\] (3)

### 3.3 Adversarial Ensemble Learning

The idea of adversarial training is to add some small but potentially misclassifying perturbations to the samples during the training process of the model, making the model adapt to such changes and thus increasing the robustness and the transferability of the model. See Section 3.3 for details. The loss function of AENet is the log-likelihood function, as shown in Equation 3.

\[
\delta = \text{arg max} \left( f_{\theta}(X + \delta), Y \right) \\
X = X + \delta \\
w(\theta) = \text{arg min} \left( X, Y \right)
\] (4)

In this paper, we select FGM adversarial training method (Miyato et al., 2017), and the perturbation parameters are calculated as shown in Equation 5, where \( g = \nabla_x \left( \text{Loss} \left( f_{\theta}(X), Y \right) \right) \).

\[
\delta = \varepsilon \cdot \left( g / \| g \| \right) \\
g = \nabla_x \left( \text{Loss} \left( f_{\theta}(X), Y \right) \right)
\] (5)

Meanwhile, during the overall training process of AENet, we optimize the model weights with the help of ensemble learning ideas and SWA model (Iznaiov et al., 2018). The final weights of the model are calculated by Equation 6, where \( n, m \) are the parameters set in advance.

\[
\bar{w}(\theta) = 1 / (n - m + 1) \sum_{i=1}^{n} w_i(\theta)
\] (6)

After incorporating adversarial training and ensemble learning into the joint framework, the whole model of ancient Chinese WS and POS tagging based on adversarial ensemble learning, namely AENet, is constructed in this paper.

### 4. Experiment

#### 4.1 Experimental Setup

The experiments in this paper are conducted on a server with Ubuntu 20.04 Linux and eight 1080Ti GPUs. The code is written in Python 3.8.5 environment using PyTorch. We carry out these experiments for the EvaHan 2022 competition. This contest is divided into two modalities: closed and open. In the closed modality, only the provided training dataset and the SikuRoBERTa pretrained model are allowed to be used. In this paper, the closed modality is selected for the experiments. Therefore, the SikuRoBERTa is used for the pre-trained language model in the AENet model framework. The parameter \( \varepsilon \) in the adversarial training is set to 1, and \( n \) in the ensemble learning is set to 5 while \( m \) is set to 1. Precision, recall, and F1 score metrics are used to evaluate the results of ancient Chinese WS and POS tagging, respectively.

#### 4.2 Dataset Description

The training data and test data involved in the experimental part of this paper are provided by the organizer of EvaHan 2022 competition. The training data is selected from Zuozhuan, an ancient Chinese work believed to date from the Warring States Period, which contains punctuation and ancient Chinese texts after WS and POS tagging, and is presented in the form of utf-8 plain text files. The training data has a total of 166142 word tokens and 194995 char tokens.

The test dataset is divided into test A and B. Test A is still extracted from Zuozhuan, which does not overlap with the training data, mainly to observe the performance of the model in the test data of the same book. Test A mainly consists of 28131 word tokens and 33298 char tokens. Test B dataset is extracted from other books, mainly to observe the performance of the model in similar text data. Its size is similar to the test A dataset.

#### 4.3 Experimental Results

In this section, CRF and SikuRoBERTa + BiLSTM + CRF models are selected as baselines, to compare with AENet model we proposed. The running results of CRF model are provided by EvaHan 2022 organizers. The experimental results for test A dataset are shown in Table 1, and the experimental results for test B dataset are shown in Table 2.
It is experimentally demonstrated that the AENet model using only adversarial training and the experimental results only show the degree of influence of adversarial training and testing. The results of the AENet model are substantially improved by introducing adversarial training. The AENet improves the robustness and generalization of the model, which effectively enhances the robustness and generalization of the model we proposed while improving the recognition efficiency of the model. The experimental results demonstrate that AENet has better performance in handling the ancient Chinese WS and POS tagging tasks, compared with baselines.

### 4.4 Ablation Study

This section focuses on the ablation analysis of the AENet model and observes the degree of influence of adversarial training and ensemble training on the robustness and generalization of the model. Therefore, we compare the model using only adversarial training, that is, AENet\(_{\text{AT}}\) and only ensemble learning, that is, AENet\(_{\text{E}}\) with the original AENet model, and the experimental results for test B dataset are shown in Table 3.

| Metric (%) | Precision | Recall | F1 score |
|------------|------------|--------|----------|
| CRF (WS)   | 90.64      | 92.08  | 91.35    |
| CRF (POS)  | 89.06      | 89.54  | 89.30    |
| PLM+BiLSTM+CRF (WS) | 95.15 | 96.07 | 95.61 |
| PLM+BiLSTM+CRF (POS) | 90.69 | 91.56 | 91.12 |
| AENet (WS) | 95.18      | 96.49  | 95.83    |
| AENet (POS) | 90.96      | 92.22  | 91.59    |

Table 1: Results for test A

| Metric (%) | Precision | Recall | F1 score |
|------------|-----------|--------|----------|
| PLM+BiLSTM+CRF (WS) | 93.49 | 90.39 | 91.91 |
| PLM+BiLSTM+CRF (POS) | 87.02 | 84.14 | 85.56 |
| AENet (WS) | 94.48      | 91.70  | 93.07    |
| AENet (POS) | 88.40      | 85.80  | 87.08    |

Table 2: Results for test B

The experimental results show that the use of the model framework of pre-training and fine-tuning substantially improved the performance of the model. In the test A dataset, compared with the baseline CRF model, AENet improves the F1 score of WS by 4.48% and the score of POS tagging by 2.29%.

In addition, we find that although the WS task of the AENet model is 0.22% higher than the SikuRoBERTa + BiLSTM + CRF model and the POS tagging task improves 0.47% in the test A, the WS task of the AENet model is 1.16% higher than the SikuRoBERTa + BiLSTM + CRF model in the test B and the POS tagging task improves by 1.52%. This is sufficient to demonstrate that the robustness and generalization of our AENet model are substantially improved by introducing adversarial ensemble learning.

## 5. Conclusion

We introduce a joint framework based on adversarial ensemble learning in this paper, namely AENet, for the task of ancient Chinese WS and POS tagging. On the basis of pre-training and fine-tuning, AENet treats WS and POS tagging as a joint sequence tagging task, and we design a joint tagging approach to reduce the error propagation and noise impact caused by individual task training. Then, AENet incorporates adversarial training and ensemble learning, which effectively enhances the robustness and generalization of the model we proposed while improving the recognition efficiency of the model. The experimental results demonstrate that AENet has better performance in handling the ancient Chinese WS and POS tagging tasks, compared with baselines.

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