AnchiBERT: A Pre-Trained Model for Ancient Chinese Language Understanding and Generation

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Abstract

Ancient Chinese is the essence of Chinese culture. There are several natural language processing tasks of ancient Chinese domain, such as ancient-modern Chinese translation, poem generation, and couplet generation. Previous studies usually use the supervised models which deeply rely on parallel data. However, it is difficult to obtain large-scale parallel data of ancient Chinese. In order to make full use of the more easily available monolingual ancient Chinese corpora, we release AnchiBERT, a pre-trained language model based on the architecture of BERT, which is trained on large-scale ancient Chinese corpora. We evaluate AnchiBERT on both language understanding and generation tasks, including poem classification, ancient-modern Chinese translation, poem generation, and couplet generation. The experimental results show that AnchiBERT outperforms BERT as well as the non-pretrained models and achieves state-of-the-art results in all cases.

1 Introduction

Ancient Chinese is the written language in ancient China, which has been used for thousands of years. There are large amounts of unlabeled monolingual ancient Chinese text in various forms, such as ancient Chinese articles, poems, and couplets. Investigating ancient Chinese is a meaningful and essential domain. Previous studies have made several attempts on it. For example, Liu et al. (2020) train a Transformer model to translate ancient Chinese into modern Chinese. Yan et al. (2016) and Yuan et al. (2019) apply an RNN-based model with attention mechanism to generate Chinese couplets. Yi et al. (2017a) generate ancient Chinese poems with RNN encoder-decoder framework. These ancient Chinese tasks often employ supervised models, which deeply rely on the scale of parallel datasets.

However, those datasets are costly and difficult to obtain due to the requirement for expert annotation. In the absence of parallel data, previous studies have proposed pre-trained language models to utilize the large-scale unlabeled corpora to further improve the model performance on NLP tasks, such as ELMo (Peters et al., 2018), GPT (Radford et al., 2018), and BERT (Devlin et al., 2019). These pre-trained models learn universal language representations from large-scale corpora with self-supervised objectives, and then are fine-tuned on downstream tasks. However, these models are trained on general-domain text which has linguistic characteristics shift from ancient Chinese text. The shift between modern Chinese and ancient Chinese is shown in figure 1.

Therefore, we propose AnchiBERT, a pre-trained language model based on the architecture of BERT, which is trained on the large-scale ancient Chinese corpora. We evaluate the performance of AnchiBERT on both language understanding and generation tasks. Our contributions are as follows:

• To our best knowledge, we propose a first pre-trained language model in ancient Chinese domain, which is trained on the large-scale ancient Chinese corpora we build.

• We evaluate the performance of AnchiBERT

Ancient Chinese

文武争驰，君臣无事，可以尽豫游之乐。

Modern Chinese

文臣武将争先恐后前来效力，国君和大臣没有大事烦扰，国君就可以尽情享受安逸的生活。

English

Civil servants and military generals work hard, then the monarch and ministers could enjoy a comfortable life without any disturbance.

Figure 1: Linguistic characteristics shift between modern Chinese and ancient Chinese.
on four ancient Chinese downstream tasks, including both language understanding and language generation tasks. AnchiBERT achieves new state-of-the-art results in all tasks which verify the effectiveness of pre-training strategy in ancient Chinese domain.

- We propose a complete pipeline to apply pre-trained model into several ancient Chinese domain tasks. We will release our code, pre-trained model, and corpora\(^1\) to facilitate the further research on ancient Chinese domain tasks.

2 Related Works

2.1 Pre-Trained Representations in General

Pre-training is an effective strategy which is widely used for NLP tasks in recent years. As static representations, Word2Vec (Mikolov et al., 2013) and GloVe (Pennington et al., 2014) are the early word-level methods to learn language representations. As dynamic representations, ELMo (Peters et al., 2018) provides the contextual representations based on a bidirectional language model. ELMo is pre-trained on huge text corpus and can learn better contextualized word embeddings for downstream tasks. GPT (Radford et al., 2018) and BERT (Devlin et al., 2019) propose pre-trained Transformer-based model to learn universal language representations by fine-tuning on large-scale corpora. Compared to GPT, BERT is trained on masked token prediction and next sentence prediction task, which extracts bidirectional information instead of unidirectional. Moreover, recent studies propose new pre-trained models, such as XLNet (Yang et al., 2019), RoBERTa (Liu et al., 2019), and ALBERT (Lan et al., 2020), which bring improvements on downstream tasks.

2.2 Domain-Specific pre-trained Models

Several studies propose pre-trained models which adapt to specific domains or tasks. BioBERT (Lee et al., 2020) is trained on large-scale biomedical text for biomedical domain tasks. SciBERT (Beltagy et al., 2019) is trained for scientific domain tasks on biomedical and computer science text, using its own vocabulary (SCIVOCAB). ClinicalBERT (Alsentzer et al., 2019) is proposed due to the need for specialized clinical pre-trained model and is applied to clinical tasks. In addition, recent studies also release monolingual pre-trained models for a specific language besides English. FlauBERT (Le et al., 2020) and CamemBERT (Martin et al., 2020) are trained for French. BERTje (de Vries et al., 2019) and RobBERT (Delobelle et al., 2020) are trained for Dutch. AraBERT (Antoun et al., 2020) is trained for Arabic language.

2.3 Ancient Chinese Domain Tasks

Ancient Chinese domain tasks include translating ancient Chinese into modern Chinese, generating poems, generating couplets, and so on. For translation, Liu et al. (2020) translate ancient Chinese into modern Chinese with a Transformer model. For poem generation, several studies are based on templates and rules (Tosa et al., 2008; Wu et al., 2009; Manurung et al., 2012). With the development of deep learning, some approaches generate poems with an encoder-decoder framework (Wang et al., 2016; Yi et al., 2017b; Liu et al., 2018). Moreover, many new model methods are applied to poem generation, such as reinforcement learning (Yi et al., 2018) and variational autoencoder (Yang et al., 2018). For couplet generation, Jiang and Zhou (2008) use a statistical machine translation approach. Yan et al. (2016) and Yuan et al. (2019) apply an RNN-based model with attention mechanism to generate couplets. However, these tasks use limited annotated data and leave the large-scale unlabeled ancient Chinese text behind. We utilize the unlabeled data to train AnchiBERT, a pre-trained model which adapts to ancient Chinese domain. AnchiBERT achieves SOTA results in all downstream tasks.

3 Method

3.1 Model Architecture

AnchiBERT exactly follows the same architecture as BERT (Devlin et al., 2019), using a multi-layer Transformer (Vaswani et al., 2017). AnchiBERT uses the configuration of BERT-base, with 12 layers, the hidden size of 768, and 12 attention heads. The total number of model parameters is about 102M.

3.2 Pre-Training Data

The ancient Chinese corpora used for training AnchiBERT are listed in Table 1. The corpora consist of articles, poems and couplets which are written in ancient Chinese, resulting in the corpora size of

\(^1\)The dataset and model will be available at https://github.com/xxxxxx
Pre-training Data

Ancient Chinese (39.5M tokens)

Weight Initialization

BERT-Base (Chinese)

Pre-training

Masked Token Prediction

Feed Forward

Add & Norm

Multi-Head Attention

Input & Position Embedding

12x

Figure 2: Overview of pre-training and fine-tuning process of AnchiBERT.

3.3 Pre-Training AnchiBERT

Instead of training from scratch, AnchiBERT continues pre-training based on the BERT-base (Chinese) model on our ancient Chinese corpora, as shown in Figure 2. We use masked token prediction task (MLM) to train AnchiBERT. Following Devlin et al. (2019), given a text sequence \( x = \{x_1, x_2, ..., x_n\} \) as input, we randomly mask 15% of the tokens from \( x \). During pre-training, 80% of those selected tokens are replaced with [MASK] token, 10% are replaced with a random token, and 10% are unchanged. The training objective is to predict the masked tokens with cross entropy loss. We do not use next sentence prediction (NSP) task because previous work shows this objective does not improve downstream task performance (Liu et al., 2019).

Following Devlin et al. (2019), we optimize the MLM loss using Adam (Kingma and Ba, 2015) with a learning rate of 1e-4 and weight decay of 0.01. Due to the limited memory of GPU we train the model with batch size of 15. The maximum sentence length is set to 512 tokens.

We adopt the original tokenization script and tokenize text based on the granularity of Chinese character, where a Chinese character denotes a token. We use the originally released vocabulary in BERT-base (Chinese).

3.4 Fine-Tuning AnchiBERT

For ancient Chinese understanding task, we apply a classification layer atop AnchiBERT. For ancient Chinese generation tasks, we use a Transformer-based encoder-decoder framework, which employs AnchiBERT as encoder and uses a transformer decoder with random initialization parameters. Details can be found in § 4.2.

4 Experiments

In this section, we first describe the pre-training details of AnchiBERT, and then introduce the task objective, dataset, settings, baselines, and metrics of each downstream task.

4.1 AnchiBERT Pre-training

AnchiBERT continues pre-training from BERT-base (Chinese) on our ancient Chinese corpora.
Table 2: Train/dev/test dataset sizes (number of pairs) of each task.

| Task   | Data(train/dev/test) |
|--------|-----------------------|
| PTC    | 2.8K/0.2K/0.2K        |
| AMCT   | 1.0M/125.7K/100.6K    |
| CPG    | 0.22M/5.4K/5.4K       |
| CCG    | 0.77M/4.0K/4.0K       |

For automatic evaluation metric, we evaluate models on classification accuracy.

4.2.2 Ancient-Modern Chinese Translation (AMCT)

Ancient-Modern Chinese Translation (AMCT) task translates ancient Chinese sentences into modern Chinese, because ancient Chinese is difficult for modern people to understand. We conduct experiments on ancient-modern Chinese dataset (Liu et al., 2020). This dataset contains 1.2M aligned ancient-modern Chinese sentence pairs, with ancient Chinese sentence as input and modern Chinese as target.

For training settings, this task is based on encoder-decoder framework. As figure 2 shows, we initialize the encoder with AnchiBERT and use a Transformer-based decoder, which is randomly initialized. Following the framework of Transformer, our decoder generates text conditioned on encoder hidden representations through multi-head attention. The training objective is to minimize the negative log likelihood of the generated text.

The training batch size and the layer number of decoder is 30 and 4, respectively. We use the same optimizer as Transformer, with $\beta_1 = 0.9$, $\beta_2 = 0.98$, $\epsilon = 1e-9$ and a linear warmup over 4000 steps. The dropout rate is 0.1. We choose the best number of epoch on the Dev set.

We compare our AnchiBERT with the following baselines:

1. Transformer-A: Transformer-A (Liu et al., 2020) is a Transformer model with augmented data of ancient-modern Chinese pairs.
2. Std-Transformer: Std-Transformer follows the framework of Transformer, with an encoder identical to Std-Transformer in § 4.2.1 and a randomly initialized decoder.
3. BERT-Base: BERT-Base follows the framework of Transformer, with an encoder identical to BERT-Base in § 4.2.1 and a randomly initialized decoder.
For automatic evaluation metric, we adapt BLEU evaluation (Papineni et al., 2002) which compares the quality of generated sentences with the ground truth. We apply BLEU-4 in this task.

We also include human evaluation for generation tasks because the above automatic evaluation metric has some flaws. For example, given an ancient Chinese sentence, there is only one ground truth. But in fact there are more than one appropriate ways of expression for modern Chinese. Thus we follow the evaluation standards in (Yan et al., 2016), and invite 10 evaluators to rank the generations in two aspects: syntactic and semantic. As for syntactic, evaluators evaluate whether the composition of translated modern Chinese is complete. As for semantic, evaluators consider whether the generated sentences are coherent and fluent. The score is assigned with 0 and 1, with 1 meaning good.

4.2.3 Chinese Poem Generation (CPG)

In Chinese Poem Generation (CPG) task, we implement two experimental settings. The first task is to generate the last two lines of a poem from the first two lines (2-2), the second task is to generate the last three lines from the first line (1-3). These four lines of a poem should match each other by following the syntactic and semantic rules in ancient Chinese poems. We use another publicly available poetry dataset for experiment, which contains 0.23M four-line classical Chinese poems.

For training settings, this task uses the same encoder-decoder framework and loss function described in §4.2.2. We apply a batch size of 80 and a 2-layer randomly initialized decoder. We use the same optimizer in §4.2.2 and fine-tune for around 60 epochs.

We compare our AnchiBERT with the following baselines:

1. RNN-based Models: We first implement the basic LSTM and Seq2Seq model. We also include SeqGAN model (Yu et al., 2017), which applies reinforcement learning into Generative Adversarial Net (GAN) to solve the problems in generating discrete sequence tokens. Furthermore, NCM (Yan et al., 2016) is an RNN-based Seq2Seq model incorporating the attention mechanism. NCM also includes a polishing schema, which generates a draft first and then refines the wordings.

2. Std-Transformer: Std-Transformer follows the framework of Transformer, with an encoder identical to Std-Transformer in §4.2.1 and a randomly initialized decoder.

3. BERT-Base: BERT-Base follows the framework of Transformer, with an encoder identical to BERT-Base in §4.2.1 and a randomly initialized decoder.

4.2.4 Chinese Couplet Generation (CCG)

Chinese Couplet Generation (CCG) task generates the second sentence (namely a subsequent clause) of couplet, given the first sentence (namely an antecedent clause) of couplet. We conduct this experiment on a publicly available couplet dataset, which contains 0.77M couplet pairs.

For training settings, we use the same model architecture and loss function described in §4.2.2. The batch size is 80 and the layer number of decoder is 4. We use the same optimizer in §4.2.2 and fine-tune for around 60 epochs.

We compare our AnchiBERT with the following baselines:

1. RNN-based Models: We first implement the basic LSTM and Seq2Seq model. We also include SeqGAN model (Yu et al., 2017), which applies reinforcement learning into Generative Adversarial Net (GAN) to solve the problems in generating discrete sequence tokens. Furthermore, NCM (Yan et al., 2016) is an RNN-based Seq2Seq model incorporating the attention mechanism. NCM also includes a polishing schema, which generates a draft first and then refines the wordings.

2. Std-Transformer: Std-Transformer follows the framework of Transformer, with an encoder identical to Std-Transformer in §4.2.1 and a randomly initialized decoder.

3. BERT-Base: BERT-Base follows the framework of Transformer, with an encoder identical to BERT-Base in §4.2.1 and a randomly initialized decoder.

For automatic evaluation metric, because the generated couplet sentences are often less than 10 tokens, we use BLEU-2 in CCG task. Meanwhile, we use the human evaluation metric in §4.2.2 to evaluate couplet in syntactic and semantic. For syntactic, the generated subsequent clauses should conform to the length and pattern rules.
| Model         | AMCT Syntactic | AMCT Semantic | CPG (2-2) Syntactic | CPG (2-2) Semantic | CPG (1-3) Syntactic | CPG (1-3) Semantic | CCG Syntactic | CCG Semantic | Average |
|--------------|---------------|--------------|---------------------|-------------------|-------------------|-------------------|-------------|-------------|---------|
| Std-Transformer | 0.63          | 0.58         | 0.69               | 0.60              | 0.67              | 0.52              | 0.61        | 0.59        | 0.61    |
| BERT-Base    | 0.69          | 0.61         | 0.72               | 0.64              | 0.67              | 0.54              | 0.63        | 0.62        | 0.64    |
| AnchiBERT    | **0.71**      | **0.62**     | **0.73**           | **0.65**          | **0.69**          | **0.55**          | **0.65**    | **0.63**    | **0.65** |

Table 3: Human evaluation results of generation tasks.

| Task      | Model       | BLEU-4 |
|-----------|-------------|--------|
| AMCT      | Transformer-A | 27.16  |
|           | Std-Transformer | 27.80  |
|           | BERT-Base    | 28.89  |
|           | AnchiBERT    | **31.22** |
| CPG (2-2) | Std-Transformer | 27.47  |
|           | BERT-Base    | 29.82  |
|           | AnchiBERT    | **30.08** |
| CPG (1-3) | Std-Transformer | 19.52  |
|           | BERT-Base    | 21.63  |
|           | AnchiBERT    | **22.10** |

Table 4: Evaluation results on AMCT and CPG tasks. For CPG task, we implement two experimental settings, including generating the last two sentences from the first two sentences (2-2) and generating the last three sentences from the first sentence (1-3).

| Task  | Model       | BLEU-2 |
|-------|-------------|--------|
| CCG   | LSTM        | 10.18  |
|       | Seq2Seq     | 19.46  |
|       | SeqGAN      | 10.23  |
|       | NCM         | 20.55  |
|       | Std-Transformer | 27.14  |
|       | BERT-Base   | 33.01  |
|       | AnchiBERT   | **33.37** |

Table 5: Evaluation results on CCG task, we apply BLEU-2 as evaluation metric.

5 Results

The experiment results are shown in tables above. Generally, we find that AnchiBERT outperforms BERT-Base as well as the non-pretrained models on all ancient Chinese domain tasks. AnchiBERT also achieves new SOTA results in all cases.

5.1 Automatic Evaluation Results

The accuracy (the higher the better) is shown in table 6 and BLEU (the higher the better) results are shown in table 4 and table 5 respectively.

Poem Topic Classification Table 6 shows AnchiBERT achieves the SOTA result in Poem Topic Classification task. AnchiBERT improves accuracy by 6.99 over BERT-Base and 12.34 over Std-Transformer. Because the scale of this task dataset is very small, the result illustrates pre-training, especially domain-specific pre-training can significantly improve performance on low-resource task.

Ancient-Modern Chinese Translation Table 4 shows AnchiBERT outperforms all the baseline models in Ancient-Mo dern Chinese Translation task. AnchiBERT raises the BLEU score by 2.33 points over BERT-Base and 3.42 over Std-Transformer, which demonstrates the effectiveness of domain-specific pre-training in language generation task.

Chinese Poem Generation AnchiBERT improves performance over two variants (BERT-Base and Std-Transformer) in both experimental settings. In CPG (2-2), AnchiBERT reaches a slightly higher score by 0.26 than BERT-Base and +2.62 than Std-Transformer. In CPG (1-3), AnchiBERT reaches +0.47 over BERT-Base and +2.58 over Std-Transformer.

Chinese Couplet Generation Table 5 shows AnchiBERT outperforms all of the non-pretrained baseline models and two variants (+0.36 over BERT-Base and +6.23 over Std-Transformer). Note that the task-specific model NCM performs better than general model Std-Transformer, which demonstrates the need for task-specific model architectures. However, the pre-trained models



9The performance of Std-Transformer (12 layers of encoder) is extremely poor for CPG (1-3), so we train a randomly initialized Transformer (6 layers of encoder) for this experimental setting and present the best result.
### Ancient-Modern Chinese Translation

| Ancient Sentence | Ground Truth | Std-Trans | Bert-Base | AnchiBERT |
|------------------|--------------|-----------|-----------|-----------|
| 小臣欲献天王赐,天子无私二十朝。 | 听学生念书。听完以后，总是默默地记住。 (After listening to other students reading books, he always carefully memorizes what they read.) | 听由诸儒生诵读书，就默默记在心里。 (He listens to other students reading books and memorizes what they read.) | 听任诸儒生诵读书，就默默记在心里。 (He listens to other students reading books, then memorizes what they read.) | 听学生诵读书，听完之后，就默默地记在心里。 (After listening to other students reading books, he always carefully memorizes what they read.) |

### Antecedent Clause

| Chinese Couplet Generation |
|----------------------------|
| 千林鸟唱，四季风和，喜看万木连春草。 (Birds sing in the forest. People are happy to see green woods and white clouds.) |

### Ground Truth

| Chinese Poem Generation (1-3) |
|------------------------------|
| **First Line** | 云重时飞雪 (It's cloudy and snowy now and then.) |
| **Ground Truth** | 春迟未见梅。山园多芋栗，夜话且燔煨。 (Spring comes late, and the plum trees are not in bloom. There are taros in the yard, and people are talking and baking together.) |
| **Std-Trans** | 春迟未见梅。山园多芋栗，夜话且燔煨。 (Spring comes late, and the plum trees are not in bloom. There are taros in the yard, and people are talking and baking together.) |
| **Bert-Base** | 春迟未见梅。山园多芋栗，夜话且燔煨。 (Spring comes late, and the plum trees are not in bloom. There are taros in the yard, and people are talking and baking together.) |
| **AnchiBERT** | 春迟未见梅。山园多芋栗，夜话且燔煨。 (Spring comes late, and the plum trees are not in bloom. There are taros in the yard, and people are talking and baking together.) |

### Table 3

Table 3 reports the human evaluation results on generation tasks. We only compare with BERT variants (Std-Transformer and BERT-Base) because we focus on the effectiveness of domain-specific pre-training. For each experiment, we collect 20 generations respectively. We invite 10 evaluators who are proficient in Chinese literature.

In general, the average results demonstrate our model AnchiBERT outperforms all variants. The syntactic scores of our pre-trained AnchiBERT show that although no templates or rules (such as rhythm and length for poem) are set in the AnchiBERT model explicitly, the model can automatic-
cally generate text conforming to these grammatical rules. The semantic scores indicate that AnchiBERT learns semantic rules during pre-training, so in downstream tasks AnchiBERT can generate more coherent text across sentences. Note that BERT-Base achieves similar scores with AnchiBERT, which demonstrates pre-training on general-domain text is efficient as well.

5.3 Samples Analysis

Figure 3 shows some samples of ancient Chinese translation, poem generation and couplet generation. In the generation tasks, we observe that the inability of Std-Transformer to learn language representation leads to the lack of coherence in generated sentences. BERT-Base learns representation from modern Chinese corpus, so it performs slightly worse for ancient Chinese. AnchiBERT is able to generate ancient Chinese sentences which is coherent and meaningful.

For example, in Ancient-Modern Chinese Translation task, ancient sentence ‘听已’ (after listening) is translated into ‘听完以后’ (after listening). However, Std-Transformer and BERT-Base ignore this sentence, whereas AnchiBERT makes the translation. In Chinese Poem Generation (2-2), the original ground truth describes the patriotism of the author. However, the generated sentences of Std-Transformer do not have this meaning. Meanwhile, the first generated sentence of BERT-Base describes the life of ordinary people, which has a semantic shift from the ground truth. AnchiBERT generates sentences which express the heavy atmosphere and the expectations for a prosperous dynasty and fit the poem topic well.

5.4 Discussion

We observe that pre-training is an effective strategy in ancient Chinese domain, not only in language understanding but also in language generation tasks. On automatic evaluation, AnchiBERT performs better than BERT-base in all ancient Chinese domain tasks, and significantly outperforms the non-pretrained models. Human evaluators also think that AnchiBERT is able to generate text which follows grammatical rules better and is more fluent for people to read.

6 Conclusion

In this paper, we release AnchiBERT, the first pre-trained language model in ancient Chinese domain to the best of our knowledge. AnchiBERT is based on BERT and trained on ancient Chinese corpora. We evaluate AnchiBERT on downstream language understanding and generation tasks, which achieves state-of-the-art performance.

There are some directions for future research. First, find a suitable learning objective during pre-training in ancient Chinese domain. Then, find more ancient Chinese data and construct an ancient Chinese domain vocabulary to train AnchiBERT.

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