Legal Transformer Models May Not Always Help

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Abstract

Deep learning-based Natural Language Processing methods, especially transformers, have achieved impressive performance in the last few years. Applying those state-of-the-art NLP methods to legal activities to automate or simplify some simple work is of great value. This work investigates the value of domain adaptive pre-training and language adapters in legal NLP tasks. By comparing the performance of language models with domain adaptive pre-training on different tasks and different dataset splits, we show that domain adaptive pre-training is only helpful with low-resource downstream tasks, thus far from being a panacea. We also benchmark the performance of adapters in a typical legal NLP task and show that they can yield similar performance to full model tuning with much smaller training costs. As an additional result, we release LegalRoBERTa, a RoBERTa model further pre-trained on legal corpora.

1 Introduction

The adoption of natural language processing in the legal domain has a long history. The earliest systems for searching online legal content appeared in the 1960s and 1970s, and legal expert systems were a hot topic of discussion in the 1970s and 1980s. Later, NLP has been applied to various legal areas to automate activities, including Natural Language Understanding based Contract review, question-answering based Legal advice. Various Natural Language tasks can be adapted to the legal domain, including

- Question Answering
- Argument detection, Definition Extraction
- Semantic Annotation
- Classification

In 2018, the release of BERT (Devlin et al., 2019) as a pre-trained language representation has achieved new state-of-the-art results on various NLP tasks. Later, on, domain-adaptive pretraining (DAPT) and task-adaptive pretraining (TAPT) (Gururangan et al., 2020) on the pre-trained model can further improve the results. Based on this idea, researchers have attempted to conduct DAPT with legal corpora, LegalBERT from (Chalkidis et al., 2020) is a good example. Later, Liu et al. (2019) argued that BERT is largely under-trained and suggested a new setup of key hyper-parameters and training schema to produce RoBERTa. RoBERTa significantly outperforms BERT’s performance on various tasks. Following the same idea as LegalBERT, we believe a further domain adaptation with RoBERTa should produce a new state-of-the-art model in the legal domain. We present LegalRoBERTa, a RoBERTa model further pre-trained on legal corpora.

However, unsupervised pretraining is a costly action that may take more than several days, even with good computing resources. (Chalkidis et al., 2020) showed that compared to BERT, legalBERT achieves only slightly better performances on three different legal NLP tasks:

- Multilabel Classification task on EU-RLEX57K dataset (Chalkidis et al., 2019)
- Multilabel Classification task on ECHR-CASES dataset (Chalkidis et al., 2019)
- Named Entity Recognition on CONTRACTS-NER dataset (Chalkidis et al., 2021)

(Micheli et al., 2020) reported that corpus-specific MLM was not beneficial on a French QuAD task. If the improvement from DAPT is not apparent compared to the original model, it is doubtful whether researchers should spend time collecting data and conducting DAPT every time a new language model is available. We tested the
popular open-source legal language models, including LegalRoBERTa produced by ourselves, to see if a significant improvement could be observed. As we will show in the section 5, both legalBERT and legalRoBERTa demonstrated a limited boost compared to the original language model in the legal text classification task.

(Wang et al., 2020) pointed out that the improvement brought by the pre-training was related to the data size of downstream tasks. The improvement is more remarkable when the downstream task is low-resource and vice-versa. As DAPT is also a particular type of pre-training; we believe that the benefit of DAPT may also have similar relationships with downstream tasks. To demonstrate this hypothesis, we tested legal language models on two different tasks: one rich resource, one low resource as well as the same task with different sizes of training data. The results showed that our hypothesis held and DAPT was especially beneficial while downstream task suffers from a lack of data.

Finally, we investigate the performance of a new NLP technique adapters in legal NLP tasks. The adapter is a more efficient way to fine-tune pre-trained language models to downstream tasks. It is faster to train and takes less space on disk. Our experimental results showed that the adapter was able to produce a comparable performance as fine-tuning the full model.

2 Contributions

The contributions of this paper are:

1. Inspired by the idea of legalBERT and the success of RoBERTa, we present legalRoBERTa, a domain-adapted language representation for the legal area. It was pre-trained on less legal corpora than legalBERT but produced a similar performance as legalBERT.

2. We adapted an existing legal summarization dataset (Galgani and Hoffmann, 2010) to a legal text retrieval task.

3. We demonstrated that current open-source legal language models could only bring marginal benefit or no improvement on a rich resource NLP task. On the other hand, We showed that DAPT was beneficial when the downstream task was low resource.

4. We tested the performance of adapters (Houlsby et al., 2019) on a legal text classification task and show that they can produce comparable results as fine-tuning the full model.

3 Related Work

(Chalkidis et al., 2020) introduced legalBERT as the first transformer adapted to the legal domain. Our work is trying to fill the gap between BERT and RoBERTa in the legal area and investigate whether DAPT is truly helpful in legal NLP tasks. (Zheng et al., 2021) reported a similar conclusion on the relation of DAPT and downstream tasks. Our work has been done simultaneously with them, and we were not aware of their results until the work is mostly finished.

4 Language Model Pre-training: LegalRoBERTa

4.1 Legal Corpora Description

| Corpus                  | Size(raw) | Size(clean) |
|-------------------------|-----------|-------------|
| Patent Litigations      | 1.57GB    | 1.1GB       |
| Caselaw Access Project  | 5.6GB     | 2.8GB       |
| Google Patents Public Data | 1.1GB   | 1.0GB       |
| Total                   | 8.3GB     | 4.9GB       |

Table 1: Pre-trained corpora

As the first step to build a legal language model, we tried to collect public law-related corpora, but there were minimal available resources. As legal documents could contain sensitive information, institutes usually only release a small part of the data to the public, and a portion of them are in PDF format. Finally, we obtained around 5 GB of clean legal text data to proceed with the domain-adaptive pre-training.

4.2 Comparison with Other corpora

| Domain | Corpus         | #Token | Size(GB) |
|--------|----------------|--------|----------|
| BIOMED | S2ORC          | 7.35B  | 47       |
| CS     | S2ORC          | 8.10B  | 48       |
| NEWS   | REALNEWS       | 6.66B  | 39       |
| REVIEW | AMAZON reviews | 2.11B  | 11       |
| LEGAL  | LEGAL-BERT     | -      | 12       |
| LEGAL  | LEGAL-ROBERTA  | 1.01B  | 4.9      |

Table 2: Corpora for various domain

Compared to other domain adaptive pre-training experiments, our legal corpora is significantly smaller.
4.3 Pre-training Details

Following (Devlin et al., 2019), we run additional pre-training steps of RoBERTa-BASE on domain-specific corpora. While (Devlin et al., 2019) suggested additional steps up to 100k, our pre-training goes up to 446k as (Chalkidis et al., 2020) suggests that prolonged in-domain pre-training brings a positive effect to future fine-tuning on downstream tasks.

Fine-tuning configuration:

- learning rate = 5e-5 (with learning rate decay, ends at 4.95e-8)
- number of epochs = 3
- Total steps = 446K
- Total flops = 2.7365e18
- Device: 2*GeForce GTX TITAN X (compute-Capability= 5.2)
- RunTime 101 hours
- Per GPU batch size = 2

Loss starts at 1.850 and ends at 0.880. The perplexity on legal corpus after domain adaptive pre-training = 2.2735.

However, given limited graphical memory space, our batch size is significantly smaller than those used in similar domain adaptive pre-training. We think further pre-training on the legal corpora should be considered and may be beneficial, c.f. Table 10.1. RoBERTa-BASE has been pre-trained for significantly more steps (1M) in generic corpora (e.g., Wikipedia, Children’s Books); thus, it is highly skewed towards generic language. (Chalkidis et al., 2020) In Appendix 10.2, we give two concrete examples to demonstrate how differently is LegalRoBERTa behaving against RoBERTa and LegalBERT from (Chalkidis et al., 2020) performance on Next-Token-Prediction task.

5 Downstream Legal NLP Tasks and Model Testing

To investigate whether legal language models are better compared with normal language models. We selected six open-source language models available on HuggingFace, including two adapted BERT models from different authors: Legal-BERT from (Chalkidis et al., 2020) and LegalBERT from (Zheng et al., 2021), one adapted RoBERTa model from us, original BERT and RoBERTa models, and finally, a randomly initialized RoBERTa model for comparison. All six models are available via HuggingFace API. Their links on HuggingFace are listed in the Table 3.

We evaluated these models on text classification and information retrieval using two different datasets. EURLEX57K (Chalkidis et al., 2019) is a large-scale multi-label text classification (LMTC) dataset of EU laws. Legal Case Reports Data Set (Dua and Graff, 2017) is a dataset containing Australian legal cases from the Federal Court of Australia (FCA) during 2006-2009, which was built to experiment with automatic summarization and citation analysis.

5.1 Large-Scale Multi-Label Text Classification on EU Legislation (rich-resource)

Experimental setup

Our dataset in this task contains 57K legislative documents from EUR-LEX, annotated with around 4.3K labels. Each document can be labeled to more than one label; thus, it is a multi-label classification task. The 4,271 labels are divided into frequent (746 labels), few-shot (3,362), and zero-shot (163), depending on whether they were assigned to more than 50, fewer than 50 but at least one, or no training documents, respectively. The model is composed of a language model as encoder and an extra classification layer on top. We use binary cross-entropy as the loss function in this task. The metrics we used in this task are identical as in the paper (Chalkidis et al., 2019).

Results

As shown in the Table 4 only Legal-BERT from (Chalkidis et al., 2020) has slightly outperformed the original BERT. The adapted model LegalBERT from (Zheng et al., 2021) is slightly below the original BERT, so is LegalRoBERTa against original RoBERTa. This slight margin could be due to statistical error because we only ran the experiments once with a fixed random seed. However, we could

| Model            | Authors                  | HuggingFace url                     |
|------------------|--------------------------|-------------------------------------|
| Legal-BERT       | (Chalkidis et al., 2020) | nlpaueb/legal-bert-base-uncased     |
| LegalRoBERTa     | Our paper                | saibo/legal-roberta-base            |
| LegalBERT        | (Zheng et al., 2021)     | zhucal/legalbert                    |
| RoBERTa-base     | (Liu et al., 2019)       | roberta-base                        |
| BERT-base-unc    | (Devlin et al., 2019)    | bert-base-uncased                   |
| rand-RoBERTa     | Our paper                | saibo/random-roberta-base           |

Table 3: Tested Language Models with HuggingFace URLs
Table 4: Results on Large-Scale Multi-Label Text Classification on EU Legislation

| Model             | Precision | Recall | F1   | R@5  | P@5  | RP@5 | NDCG@5 |
|-------------------|-----------|--------|------|------|------|------|--------|
| Legal-BERT        | 0.86      | 0.63   | 0.73 | 0.72 | 0.69 | 0.79 | 0.82   |
| LegalRoBERTa      | 0.84      | 0.63   | 0.72 | 0.70 | 0.67 | 0.78 | 0.80   |
| LegalBERT         | 0.86      | 0.61   | 0.71 | 0.71 | 0.68 | 0.78 | 0.81   |
| RoBERTa-base      | 0.85      | 0.65   | 0.74 | 0.72 | 0.69 | 0.79 | 0.82   |
| BERT-base-uncased | 0.86      | 0.62   | 0.72 | 0.72 | 0.69 | 0.79 | 0.82   |
| random-RoBERTa    | 0.85      | 0.59   | 0.69 | 0.69 | 0.66 | 0.76 | 0.79   |

Only Legal-BERT from (Chalkidis et al., 2020) has slightly outperformed original BERT. The adapted model from (Zheng et al., 2021) is slightly below the original BERT, so is legalRoBERTa against original RoBERTa.

| Split   | Documents(D) | Words/D | Labels/D |
|---------|--------------|---------|----------|
| Train   | 45k          | 729     | 5        |
| Dev     | 6k           | 714     | 5        |
| Test    | 6k           | 725     | 5        |
| Total   | 57k          | 727     | 5        |

Table 5: Statistics of the EUR-LEX dataset

We use a supervised approach to rank and retrieve catchphrases from court case documents. Our method is inspired by VSE++: Improving Visual-Semantic Embeddings with Hard Negatives from (Faghri et al., 2018). In that work, image-caption retrieval was conducted using image-caption embedding similarity rank, on which the model is optimized via the minimization of triplet ranking loss. We applied the same idea to our catchphrase retrieval task by replacing the images with case descriptions and captions with catchphrases. An essential difference between this task and the previous task is the volume of training data. Comparing the Table 7 and Table 5, the retrieval task has only $\frac{1}{10}$ training data as the text classification task.

As shown in the Figure 10.3, the model in this task consists of an encoder (pre-trained transformer in our case) to extract features from both catchphrases and documents plus a dense neural network to transform features to representation in a shared space. The loss function in this task is the triplet loss function. Moreover, as we have only one ground true catchphrase, our task is roughly five times more difficult than the popular MS-COCO image-captioning task, where each image has five ground true captions on average.

The metric we used in this task is Recall@K (R@K), Mean Rank of the ground-true label, and median rank of the ground-true label (MeanRank and MedRanks are the lower, the better). We notice that this metric also depends on the size of the test database. For example, searching over a one-thousand cases test set is more challenging than a one-hundred cases test set. In this project, we focus on the test set of size $= 389$ cases.

Results

As showed in the Table 8, all the domain-pre-
Table 6: Improvement on LMTC with different sizes of training data

| Split | Cases | Train | Dev | Test | Total |
|-------|-------|-------|-----|------|-------|
| 100%  | 45000 | 2807  | 350 | 350  | 3507  |
| 20%   | 9000  | 2807  | 350 | 350  | 3507  |
| 10%   | 4500  | 2807  | 350 | 350  | 3507  |
| 5%    | 2250  | 2807  | 350 | 350  | 3507  |
| 1%    | 450   | 2807  | 350 | 350  | 3507  |

Table 7: Statistics of the AUS-CASE dataset

| Model     | R1   | R5   | R10  | MedRank | MeanRank |
|-----------|------|------|------|---------|----------|
| BERT      | 14.4 | 33.7 | 45.7 | 13.0    | 49.8     |
| +DAPT     | +0.6 | +0.8 | +0.4 | +0.0    | +1.1     |
| RoBERTa   | 13.6 | 33.1 | 44.7 | 14.0    | 55.5     |
| +DAPT     | +0.6 | +0.8 | +0.9 | +0.0    | +2.9     |
| Legal-BERT| 16.8 | 37.7 | 49.9 | 10.6    | 46.9     |
| +DAPT     | +1.0 | +0.5 | +0.3 | +0.6    | +1.3     |
| LegalBERT | 15.4 | 34.8 | 46.2 | 12.8    | 47.3     |
| +DAPT     | +0.2 | +1.3 | +1.1 | +0.4    | +1.8     |
| LegalRoBERTa | 15.1 | 34.6 | 46.3 | 13.5    | 52.9     |
| +DAPT     | +1.1 | +0.9 | +0.8 | +1.0    | +0.4     |

Table 8: Results on Automatic Catchphrase Retrieval from Legal Court Case Documents

trained models have outperformed the corresponding original model. Legal-BERT from (Chalkidis et al., 2020) is significantly better than the original BERT. This result suggested that domain-adapted models should be favored in the case of low-resource tasks.

6 Varying Downstream task data size

Based on the observation from the previous experiments, we further investigate the relation between domain-pretraining and downstream task data size. We vary the size of training data of LMTC tasks and compare the performance of BERT versus LegalBERT (see Table 10.5).

The results in Table 6 show that domain-pretraining’s performance improvement is tightly related to the downstream task training data size. The benefit is significant when the training data is scarce and negligible when the training data is sufficient.

7 Adapters in legal text classification

When there are multiple downstream tasks, it is time-wise inefficient to fine-tune the whole language model once per task, and it also requires much space to save the models for each task. Adapter proposed by (Houlsby et al., 2019) is a good alternative to full model fine-tuning. Instead of updating all the parameters contained in the model, we add a so-called adapter module into the model. In the training step, only parameters contained in the adapter module are updated while the language model itself remains unchanged. When training is finished, one only needs to save the adapter module for each task.

This multi-task scenario is frequent in legal NLP tasks because a legal activity could be assisted by several relatively simple downstream tasks. We test the adapter module on various language models with or without domain pre-training. From the performance perspective, adapters can produce the same results as fine-tuning the whole model, cf Table 9. However, training adapters is not faster than fine-tuning the full model because the forward pass and back-propagation still have a similar amount of calculations as fine-tuning the whole model.

8 Limitations and Future Work

The size of legal corpora available restricted the pre-training of LegalRoBERTa. To better utilize the potential of RoBERTa, we should consider collecting more data such as automatic scraping. In the meantime, (Chalkidis et al., 2020) has released some other legal corpora of UK and EU legislative
| Model          | Precision | Recall | F1  | R@5  | P@5  | RP@5 | NDCG@5 |
|---------------|-----------|--------|-----|------|------|------|--------|
| Legal-BERT    | 0.86      | 0.63   | 0.73| 0.72 | 0.69 | 0.79 | 0.82   |
| Adapter (diff)| +0.01     | -0.03  | -0.02| -0.01| -0.01| 0.0  | 0.0    |
| LegalRoBERTa  | 0.84      | 0.63   | 0.72| 0.70 | 0.67 | 0.78 | 0.80   |
| Adapter (diff)| -0.02     | -0.04  | -0.02| 0.0  | 0.0  | 0.0  | 0.0    |
| LegalBERT     | 0.86      | 0.61   | 0.71| 0.71 | 0.68 | 0.78 | 0.81   |
| Adapter (diff)| -0.01     | 0.0    | 0.0 | 0.0  | 0.0  | +0.01| 0.0    |
| RoBERTa-base  | 0.85      | 0.65   | 0.74| 0.72 | 0.69 | 0.79 | 0.82   |
| Adapter (diff)| +0.01     | -0.06  | -0.04| -0.01| -0.01| 0.00 | -0.01  |

Table 9: Performance of adapters on LMTC task

of roughly 2.5 GB. It should be beneficial to include those data into the pre-training of LegalRoBERTa v2. Furthermore, the pre-training steps seem to be insufficient compared with other related work (see 10.1). In the task of Large-Scale Multi-Label Text Classification on EU Legislation, we evaluated models with identical hyper-parameters due to limited time and limited computing resources. A grid search of hyper-parameters and repeated experiments several times with different random seeds could be considered.

In the task of legal case retrieval, paired statistical testing can be conducted to conclude whether the domain pre-trained models are significantly better than the original models.

9 Conclusion

In this work, we first tried to answer a critical question in legal NLP from an empirical perspective: When does domain pre-training help the model to yield better performance? Through a series of legal NLP experiments, we showed that the existing three legal transformer models did not yield significant improvement on a rich-resource task while did show considerable improvement on a low-resource task or if we deliberately cut down the training data size. We therefore recommend domain pre-trained language models only in case of low-resource tasks. The second part showed that adapters, as an emerging technique, are very suitable to solve legal NLP tasks. As an intermediate result, we release LegalRoBERTa1, a Roberta model adapted to the legal domain.

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Appendix

10.1 Domain Adaptive Pre-training Details of Related Work

In the table below, we can see the Domain Adaptive Pre-training details of related work.

| Experiment       | Authors                  | Step  | # epoch | batch size |
|------------------|--------------------------|-------|---------|------------|
| Various Domains  | (Gururangan et al., 2020)| 12.5K | 1       | 256        |
| LegalBERT        | (Chalkidis et al., 2020)| 1000K | 40      | 256        |
| BioBERT          | (Lee et al., 2019)       | 200K-470K | -     | 192        |
| LegalROBERTa     | Our paper                | 446K  | 3       | 4          |

10.2 Examples of Next-Token-Prediction Results of LegalRoBERTa

This \{mask\} Agreement is between General Motors and John Murray.

| Model            | Top1  | Top2   | Top3   |
|------------------|-------|--------|--------|
| BERT             | new   | current| proposed|
| LegalBERT        | settlement | letter | dealer |
| LegalROBERTa     | License | Settlement | Contract |

Table 10: Next Token Prediction Example 1

The applicant submitted that her husband was subjected to treatment amounting to \{mask\} whilst in the custody of Adana Security Directorate.

| Model            | Top1     | Top2 | Top3    |
|------------------|----------|------|---------|
| BERT             | torture  | rape | abuse   |
| LegalBERT        | torture  | detention | arrest |
| LegalROBERTa     | torture  | abuse | insanity |

Table 11: Next Token Prediction Example 2

10.3 Model Architecture in Catchphrase Retrieval task

Below is an illustration of the Automatic Catchphrase Retrieval from Legal Court Case Documents described in Section 5.2.
10.4 Hyper-parameters in LMTC task
1. lr: 3e-05
2. random seed: 0
3. batch size: 16
4. max sequence size: 216
5. epochs: 40
6. dropout: 0.1
7. early stop: yes
8. patience: 7

10.5 Results on LMTC with different sizes of training data

The results on LMTC for BERT and LegalBERT with different sizes of training data are shown in the table below.

| Training data ratio | Train samples | Model    | Precision | Recall | F1   | R@5  | P@5  | RP@5 | NDCG@5 |
|---------------------|---------------|----------|-----------|--------|------|------|------|------|--------|
| 100%                | 45000         | BERT     | 0.86      | 0.62   | 0.72 | 0.72 | 0.69 | 0.79 | 0.82   |
|                     |               | LegalBERT| 0.86      | 0.63   | 0.73 | 0.72 | 0.69 | 0.79 | 0.82   |
| 20%                 | 9000          | BERT     | 0.66      | 0.19   | 0.29 | 0.39 | 0.35 | 0.43 | 0.46   |
|                     |               | LegalBERT| 0.70      | 0.19   | 0.29 | 0.40 | 0.35 | 0.43 | 0.46   |
| 10%                 | 4500          | BERT     | 0.58      | 0.15   | 0.30 | 0.27 | 0.33 | 0.35 | 0.37   |
|                     |               | LegalBERT| 0.64      | 0.18   | 0.32 | 0.28 | 0.34 | 0.37 | 0.37   |
| 5%                  | 2250          | BERT     | 0.49      | 0.11   | 0.22 | 0.20 | 0.24 | 0.26 | 0.26   |
|                     |               | LegalBERT| 0.49      | 0.13   | 0.24 | 0.22 | 0.26 | 0.26 | 0.28   |
| 1%                  | 450           | BERT     | 0.00      | 0.00   | 0.03 | 0.02 | 0.03 | 0.04 | 0.02   |
|                     |               | LegalBERT| 0.00      | 0.00   | 0.04 | 0.03 | 0.04 | 0.04 | 0.04   |