Pre-training Transformers on Indian Legal Text

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Abstract

Natural Language Processing in the legal domain has benefited hugely by the emergence of Transformer-based Pre-trained Language Models (PLMs) pre-trained on legal text. There exist PLMs trained over European and US legal text, most notably LegalBERT. However, with the rapidly increasing volume of NLP applications on Indian legal documents, and the distinguishing characteristics of Indian legal text, it has become necessary to pre-train LMs over Indian legal text as well. In this work, we introduce transformer-based PLMs pre-trained over a large corpus of Indian legal documents. We also apply these PLMs over several benchmark legal NLP tasks over both Indian legal text, as well as over legal text belonging to other domains (countries). The NLP tasks with which we experiment include Legal Statute Identification from facts, Semantic segmentation of court judgements, and Court Judgement Prediction. Our experiments demonstrate the utility of the India-specific PLMs developed in this work.

1 Introduction

Pre-trained Language Models (PLMs) learn to estimate (or, understand) natural language, so that they can be used to improve natural language tasks which inherently require a sophisticated understanding of the underlying language (Dai and Le, 2015; Howard and Ruder, 2018). PLMs are usually operated under a pre-train – fine-tune paradigm of transfer learning, where the untrained language model (LM) is first trained on an unlabeled corpus (pre-training), before applying them to a downstream task with a labeled corpus (fine-tuning), such as Natural Language Inference (Conneau et al., 2017) and Machine Translation (McCann et al., 2017).

The introduction of transformer-based PLMs and architectures such as BERT (Devlin et al., 2019) has accelerated research in the Natural Language Processing (NLP). In fact, pre-training language models on large corpora (which can be thought to be like large swaths of unlabeled text) have shown to be effective in many downstream tasks. This has led to a family of transformer based PLMs such as RoBERTa (Liu et al., 2019), XLNet (Yang et al., 2019), Longformer (Beltagy et al., 2020), and so on.

However, most of the early advancements in this paradigm of pre-training followed by fine-tuning have been in general (open) domain tasks, which generally consist of general language-based inputs. But this ability of PLMs to generalize to end-tasks has been relatively limited in specialized domains such as finance and law, mainly due to the fact that PLMs such as BERT (Devlin et al., 2019) have been trained on general domain text. Domain-specific texts often have different patterns, structures and semantics, which cannot be captured from general domain text and thus domain-specific pre-training has become popular lately (Beltagy et al., 2019; Lee et al., 2019).

Particularly, NLP is increasingly being applied in the legal domain Zhong et al. (2020), and naturally there have been efforts to develop PLMs for the legal domain. Chalkidis et al. (2020) pre-trained BERT-base on legal documents from EU, UK and US. This model has been shown to be effective in many downstream legal tasks, such as text classification, summarization and named entity recognition, among others. Again, Zheng et al. (2021) pre-trained BERT-base on only US case law documents, which was shown to improve performance over US legal datasets such as CaseHOLD. More recently, Henderson et al. (2022) pre-trained BERT-large on ‘Pile of Law’ (PoL), a huge legal corpus of US and EU documents. Although all these three models were named as LegalBERT in the original research papers, we shall address them as LegalBERT (Chalkidis et al., 2020), CaseLawBERT (Zheng et al., 2021) and PoLBERT (Henderson et al., 2022) respectively, for sake of comprehension.
Lawformer model (Xiao et al., 2021), pre-trained on Chinese legal text, has been designed keeping in mind that legal documents are usually much longer than documents in the general domain.

With the advent of digitization and image processing technologies, a lot of legal data has become readily available in digital format across many countries, like India. This has led to several new studies and technologies being developed on Indian legal data in recent years (Bhattacharya et al., 2019b,a; Malik et al., 2021; Paul et al., 2022; Kalamkar et al., 2021). Using BERT off-the-shelf for these tasks has been shown to be limited in performance, and although LegalBERT improves upon BERT across many such tasks, there is still scope for improvement in tasks of Indian legal text. This has to do particularly with the differences in the nature of Indian legal texts vis-a-vis EU and US legal texts (Kalamkar et al., 2021; Bhattacharya et al., 2019a). For instance, Indian legal documents are full of terms that are not English, such as ‘Tehsildar’ (Collector), ‘Daroga’ (Constable), and so on. Understanding these terms can be crucial depending on the particular case and the intended application. Also, there is extensive use of very long, complex sentences, with a lot of punctuation marks as mid-sentence demarcations. Finally, due to typographical or scanning errors, there are a lot of instances of missing spaces and punctuation marks, which lead to wrong words. Thus, it is beneficial to pre-train LMs over Indian legal text, allowing the model to observe such patterns during pre-training, so that performance over end-tasks over Indian legal text improves.

In this work, we conduct pre-training experiments with PLMs on a large Indian legal corpus. We collected a large corpus of court judgment documents from the Supreme Court and many High Courts of India, along with a collection of all Central Government Acts (statutory documents). Our dataset is decently positioned in terms of the number of documents (~5.4M) and size (~27GB) as compared to other pre-training datasets used in the legal domain (see Table 1). We pre-train BERT-based LMs on this corpus and estimate the efficacy of domain-specific pre-training on a number of downstream end-tasks on both Indian legal documents as well as legal documents from other countries/domains.

Our Contributions: (i) We trained two publicly available pre-trained BERT-based legal language models, namely LegalBERT (Chalkidis et al., 2020) and CaseLawBERT (Zheng et al., 2021) on a large corpus of Indian legal corpus. Both the Indian PLM variants – which we name InLegalBERT and InCaseLawBERT respectively – outperform their source LMs in terms of perplexity on Indian data. (ii) We compare between these two Indian legal PLMs, as well the original LegalBERT and CaseLawBERT, on several practically important end-tasks, namely, (1) Legal Statute Identification, (2) Semantic Segmentation of judgements, and (3) Court Judgement Prediction. We perform experiments on benchmark datasets for these tasks, comprising of text from the Indian judiciary. We further try out end-tasks on legal text from other countries, e.g., Legal Statute Identification on European Court of Human Rights (ECtHR) cases, and Semantic Segmentation on UK Supreme Court case documents. Our experiments broadly show that InLegalBERT achieves appreciable gains over LegalBERT across all tasks (while the gains are minimal for InCaseLawBERT over CaseLawBERT). Also, InLegalBERT outperforms all other variants (at least numerically) across all the end-tasks that we experimented with. These results show that further pre-training on Indian legal data helps in performance over English-language legal text datasets from other countries as well.

We make the following pre-trained language models (trained over legal text from India as well as other countries) publicly available: InLegalBERT – https://huggingface.co/law-ai/InLegalBERT InCaseLawBERT – https://huggingface.co/law-ai/InCaseLawBERT We invite the research community to apply these models on different end-tasks.

2 Related Work

Transformer-based LMs: After the introduction of the self-attention based Transformer mechanism (Vaswani et al., 2017), we have seen the widespread development of large-scale, pre-trained language models. Devlin et al. (2019) first introduced BERT, a multi-layer transformer architecture for language modeling. They used the Masked Language Modeling (MLM) objective (Taylor, 1953) to mask some tokens randomly in the text, to effectively train a deep bidirectional language model on general domain corpora, specifically English Wikipedia and BookCorpus (Zhu et al., 2015). They also
used Next Sentence Prediction (NSP) objective to sample pairs of contiguous sentences. Their proposed approach of transfer learning differed from prior works in the sense that most earlier works used to transfer pre-trained embeddings for the end tasks, whereas BERT proposed transferring the pre-trained model instead.

The unprecedented success of BERT on a range of downstream NLP tasks such as GLUE (Wang et al., 2018) and SQUAD (Rajpurkar et al., 2016) prompted research in transformer based PLMs. RoBERTa (Liu et al., 2019) used a much larger pre-training corpus and did away with the NSP objective, going for larger batch sizes instead. XLNet (Yang et al., 2019) modified the pre-training objective to Permutation Language Modeling. Longformer (Beltagy et al., 2020) introduced a global-local attention mechanism to deal with longer sequences. All these models were shown to outperform BERT on many general domain downstream tasks.

Pre-training on Specialized Domains: However, these general domain models generally did not perform so well on downstream tasks in specialized domains such as healthcare and law. Thus, efforts were dedicated to further either re-train models like BERT (continue pre-training from the BERT checkpoint) or pre-train them on specialized domain data with customized tokenizers, etc. Lee et al. (2019) tried re-training BERT for 500k and 1M steps on the biomedical domain, resulting in the model BioBERT. Meanwhile, for SciBERT (Beltagy et al., 2019), a family of models based on Scientific Text, training from scratch with custom vocabulary was preferred.

PLMs for the Legal Domain: In recent years, a lot of legal tasks and datasets have been released for multiple legislations, such as US, EU, China, India and so on. This has led to use of pre-trained transformer based models such as BERT on these datasets. However, the legal text being very unique and requiring handling of issues as described in Section 1, there is significant scope of improvement over these models, pre-trained on the general domain. There have been efforts to pre-train transformers on the legal domain: (i) Chalkidis et al. (2020) pre-trained BERT-base on EU and UK legislation and court documents from the US, European Court of Justice (ECJ) and European Court of Human Rights (ECtHR), and released the LegalBERT model; (ii) Zheng et al. (2021) proposed CaseLawBERT, pre-trained on a corpus of US case law documents and contracts; (iii) Henderson et al. (2022) prepared a huge corpus of US, Canada and EU documents (not just case law), called Pile of Law, and trained BERT-large on the same to yield the PoLBERT model; (iv) Xiao et al. (2021) released Lawformer, a Longformer (Beltagy et al., 2020) based model pre-trained on Chinese legal text. The details of the pre-training datasets are available in Table 1.

### Table 1: Pre-training datasets used in the legal domain

| Model              | Data Source                                                                 | #Documents | Size (GB) |
|--------------------|------------------------------------------------------------------------------|------------|-----------|
| LegalBERT          | EU, UK, US legislation, cases from ECJ, ECtHR                               | 350K       | 12        |
| CaseLawBERT        | Harvard Case Law (based on US federal and state courts)                     | 3.4M       | 37        |
| PoLBERT            | Legal Analyses, Court Opinions, Government Publications, Contracts, Statutes, Regulations, and more from US and EU | 10M        | 256       |
| Lawformer          | China Judgment Online (based on cases from Chinese Courts)                  | 22.7M      | 84        |
| InLegalBERT, InCaseLawBERT (this work) | Cases from Indian Supreme Court and High Courts | 5.4M | 27 |

For building the pre-training corpus of Indian legal text, we collected a large corpus of case documents from the Indian Supreme Court and many High Courts of India. These documents were collected from diverse publicly available sources on the Web, such as official websites of these courts (e.g., the website of the Indian Supreme Court: https://main.sci.gov.in/), the erstwhile website of the Legal Information Institute of India, the popular legal repository https://www.indiankanoon.org, and so on. The court cases in our dataset range from 1950 to 2019, and belong to all legal domains, such as Civil, Criminal, Constitutional, and so on. Additionally, we collected 1,113 Central Government Acts, which are the documents codifying the laws of the country. Each Act is a collection of related laws, called Sections. These 1,113 Acts contain a total of 32,021
In total, our dataset contains around 5.4 million Indian legal documents (all in the English language). The raw text corpus size is around 27 GB. A brief comparison of our dataset with other legal pre-training datasets are given in Table 1.

### 3.1 Pre-Processing

Case documents are long, structured pieces of text, and understanding the document structure can be essential for both pre-training and fine-tuning tasks. However, as discussed in Section 1, Indian legal text is known to be noisy, and is mostly written without any structure, which makes it challenging to extract the document hierarchy.

Indian court case judgements are often divided into numbered points, which can be thought of as individual segments. Each such point/segment is further subdivided into paragraphs and sentences. We used Regular Expression matching to identify segment and paragraph boundaries. Demarcating sentences in legal documents can be difficult (Savelka et al., 2017). We used the SpaCy sentencizer (Montani et al., 2020) for this purpose, customizing it with a set of abbreviated terms frequently seen in Indian legal documents (such as Rs., Smt., I.P.C., etc.). The performance of sentence splitting improved massively upon using the India-specific abbreviations, according to a manual inspection that we carried out internally.

### 4 Pre-training Setup

For both pre-training and fine-tuning tasks, we used the datasets package (Lhoest et al., 2021) by HuggingFace (HF) for dealing with loading, tokenizing and formatting. We also used the transformers package (Wolf et al., 2020) by HF to load the models and run training and evaluation tasks.

**Splitting corpus into train and test splits:** First, we split the entire corpus into train and test splits. We include all the Acts in our training split. The case documents were distributed randomly into the splits in the ratio of 9:1.

**Creating individual train and test examples:** To create individual training and testing examples, we first divided each document into multiple chunks. For documents in both train and test dataset, we divided each document into a set of equal-sized disjoint chunks of contiguous text, disrespecting sentence boundaries. Each chunk is a unique training example. This process helps us train on longer sequences, while reducing training time, as done by BERT. The method described above gives us a total of 21.6M training examples, and 2.4M testing examples.

**Training objectives:** We use the standard MLM and NSP training objectives. We use both dynamic masking for MLM and dynamic sampling for NSP, meaning that the choice of masked words (MLM) and negative samples (NSP) are not fixed beforehand in a static way, rather is dynamically chosen when a mini-batch is being built. For each training example (which is a chunk of a document, as stated above), we either pair it up with its consecutive chunk (positive sample) or randomly choose any other chunk from the same document (negative sample) in a 1:1 ratio. This gives us the sequence pair for the NSP task. Then, for each such pair of chunks, we randomly choose 15% tokens across both sequences as mask candidates. We use whole-word masking, i.e., ensuring that candidate tokens are chosen in a manner where all word-piece tokens of a real word are chosen, or none at all. Out of all such candidate tokens, we replace them with the [MASK] token 80% of the time, keep them unchanged 10% of the time, and replace them with a random token in the vocabulary 10% of the time. The masked sequence pair is passed to the BERT model. From the BERT outputs, we use the output embeddings of every token from the last encoder layer for MLM. For NSP, we use the BERT pooler output, which is basically the output embedding of the [CLS] token further passed through a feed-forward network with tanh activation. Both MLM and NSP are trained using the Categorical Cross Entropy Loss.

**Implementation Details:** We conduct two independent pre-training experiments, by starting with the two existing pre-trained models – LegalBERT (Chalkidis et al., 2020) and CaseLaw-BERT (Zheng et al., 2021) – and continuing the pre-training on our Indian dataset (Re-training). We name the two final models (after re-training on the Indian dataset) as InLegalBERT and InCaseLawBERT respectively.

Both the above models are based on the BERT-
base-uncased model (12 layers, 768 hidden dimensionality, 12 attention heads, 110M parameters). Due to the constraints on input lengths of BERT-based models, all chunks are limited to 512 tokens (including special [CLS] and [SEP] tokens). To make sure that most training information is protected from truncation, we chunk training documents into segments of 254 tokens each. Thus, while sampling pairs for NSP, we ensure the total length of the sequence pair is limited to 512.

We used a single RTX A6000 (48 GB) GPU for the pre-training. We used a batch size of 32 sequence pairs, and 8 gradient accumulation steps, making the effective batch size 256. We trained each model for a total of 300K optimization steps, which is roughly around 4 epochs of the training data. We used the default AdamW optimizer (Loshchilov and Hutter, 2019) with initial learning rate of 5e-5. We also used other techniques to speed up training, such as fp16 training, pinning the CPU memory for GPU transfer, and using 8 CPU workers for preparing the batches. In our setup, each training experiment took approximately 20 days, and each testing experiment took more than 6 hours.

**Evaluation of pre-training:** To get an idea of the quality of pre-training, we evaluate the pre-trained models on the test set (10% of the corpus, as stated earlier). We evaluate the language modeling capabilities of the models using the perplexity metric $P = e^{L_{\text{MLM}}}$, where $L_{\text{MLM}}$ represents the Cross Entropy Loss only for the MLM task over the test set.

Table 2 shows the perplexity values of the various models over our test set. All the pre-trained legal models demonstrate their greater understanding of the legal language by outperforming BERT massively in terms of perplexity. Importantly, after pre-training on Indian legal text, we observe lower perplexities for the Indian variants InLegalBERT and InCaseLawBERT, as compared to the original PLMs. In particular, InLegalBERT seems more adaptable to the Indian scenario (lower perplexity) as compared to InCaseLawBERT.

### 5 Application on end-tasks

We now apply (fine-tune) the pre-trained models on several practically important and benchmark end-tasks over both Indian legal text as well as legal text from other domains/countries. While these end-tasks may eventually require more complex architectures, however, all such architectures contain an inherent BERT-based encoder module for encoding the text either in parts or full. We try out the different PLMs as this encoder module.

For comparison, we chose the standard BERT-base (Devlin et al., 2019), the original LegalBERT (Chalkidis et al., 2020) and the original CaseLawBERT (Zheng et al., 2021) as baselines. The latter two models are based on the same architecture as BERT-base. For the sake of fair comparison, we did not choose PoLBERT (Henderson et al., 2022) as a baseline since it is based on BERT-large, which is inherently more powerful.

For each end-task, we choose one common architecture, and replace the BERT encoder module in it with BERT-base, LegalBERT, CaseLawBERT or our pre-trained models InLegalBERT or InCaseLawBERT, and then compare the performances of the models. This procedure ensures that any difference in the performances is strictly due to the PLM being used in the encoder module.

#### 5.1 Legal Statute Identification (LSI)

In countries that follow some notion of the Civil Law System, there are written laws (statutes) that guide jurisdiction. In court cases of such systems, one or more of these laws are cited, based on their relevance to the facts (evidences) of the case. The task of Legal Statute Identification (LSI) aims to automatically identify the relevant statutes (i.e., the statutes that may have been violated) given the facts of the case. LSI is a widely studied task, and is often categorized as a sub-task of the larger problem of Legal Judgment Prediction. It can be modeled as a multi-label text classification task.

#### 5.1.1 Datasets

We use two different datasets for this task:

- **ILSI:** The Indian Legal Statute Identification (ILSI) Dataset based on criminal case documents.

| Model             | Perplexity |
|-------------------|------------|
| BERT              | 25.7600    |
| LegalBERT         | 7.1331     |
| CaseLawBERT       | 11.1798    |
| InLegalBERT       | 5.2547     |
| InCaseLawBERT     | 8.7824     |

Table 2: Quality of pre-training measured via perplexity. All perplexity values reported over our test set (10% of the Indian legal text corpus).
Table 3: Performance over the ILSI and ECtHR-B datasets for Legal Statute Identification task. All reported values are macro-averaged and in terms of percentage.

| Encoder Module          | ILSI dataset | ECtHR-B dataset |
|------------------------|--------------|-----------------|
|                        | mP  | mR  | mF1 |    | mP  | mR  | mF1 |
| BERT                   | 82.12| 49.07| 59.11| 77.50|69.31|72.95|
| LegalBERT              | **83.98**| 53.83| 63.89| 80.85|70.76|75.09|
| CaseLawBERT            | 82.89| 54.72| 64.53| 82.37|66.45|72.87|
| InLegalBERT            | 82.42| 55.16| **64.58**| **83.93**|71.41|**75.88**|
| InCaseLawBERT          | 81.07| **55.64**| 64.44| 77.35|69.45|72.86|

from India (Paul et al., 2022). The dataset consists of 65K examples, split into train, dev and test splits, and a target set of 100 statutes. The facts are derived from criminal court cases from the Supreme Court and 6 High Courts of India. All 100 statutes (class labels) are part of the Indian Penal Code, which contains the defined laws for most criminal procedures in India. More details of the dataset are available in (Paul et al., 2022).

(ii) **ECtHR-B**: This is the dataset used in the ECtHR Task B from the LexGlue benchmark suite (Chalkidis et al., 2022). The ECtHR-B dataset consists of 11K examples (facts from cases argued in the European Court of Human Rights), split into train, dev and test. The label set consists of 10 articles from the European Convention of Human Rights, which mainly contain provisions on human rights issues. Each fact is mapped with the allegedly violated articles from this label set.

### 5.1.2 Models
We use the HierBERT architecture for this purpose. Specifically, for a given example, we individually pass all of its sentences to a pre-trained BERT-based model, which forms the lower-level encoder in the hierarchical setup, and extract the [CLS] representations from all of these. We then aggregate the sentence embeddings using a higher-level LSTM encoder coupled with Bahdanau’s attention. The finally aggregated embedding (representing the entire text) is then passed to a fully-connected layer with sigmoid activation for classification. Weighted Binary Cross Entropy Loss is used for training.

We limit the sentence length to 128 tokens, and use a maximum of 128 sentences per example. All intermediate embeddings (for LSTM encoder, etc.) are of dimensionality 768. We use an effective batch size of 64 and train for 20 epochs. Different initial learning rates are set for different layers (5e-3 for topmost FC layer, 1e-3 for intermediate LSTM and attention layers and 1e-5 for the lower-most BERT layers).

We run 5 variations of the architecture described above, with the lower-level encoder of each version comprising of one of the PLMs discussed earlier (BERT, LegalBERT, CaseLawBERT, InLegalBERT and InCaseLawBERT). Apart from the lower-level encoder, all the 5 variations are identical in all other aspects. The entire training setup is kept the same for both datasets.

### 5.1.3 Results
We report Macro-Precision (mP), Macro-Recall (mR) and Macro-F1 (mF1) metric for comparing the performance of different architectures (which implies, the performance of different PLMs in the encoder module, since the architectures are identical in all other aspects). The results over both the datasets are shown in Table 3.

For the ILSI dataset, the vanilla BERT model, which was pre-trained over only general domain data, performs the poorest across all metrics. LegalBERT leverages the pre-trained knowledge of legal data (albeit of a different country), and obtains massive gains over BERT. It also obtains the highest Precision score. However, CaseLawBERT does even better in terms of F1 over LegalBERT. This scenario changes for the ECtHR-B dataset, where we see LegalBERT outperforming CaseLawBERT by some margin. This might be due to the fact that although CaseLawBERT has been trained for more steps on a much larger dataset of US legal documents (helping it to generalize better for the Indian domain), LegalBERT has been trained on ECtHR documents, and thus performs better for the ECtHR-B dataset.

Injecting India-specific legal knowledge further boosts results for InLegalBERT across both datasets. Although Precision reduces slightly from the vanilla LegalBERT on the ILSI dataset, there are significant improvements for both Recall, and
more crucially, F1 score. There is an outright improvement achieved by InLegalBERT across all metrics for the ECTHR-B dataset. However, InCaseLawBERT shows a slight drop in F1 for both datasets with increase in Recall. This shows that LegalBERT is more adaptable to further pre-training on data from other countries.

Comparison with the original works: The original work (Paul et al., 2022) that introduced the ILSI dataset, employed an architecture (called LeSICiN) which is a hybrid of text-based and graph-based encodings. In particular, they used a Sent2vec encoder (Moghadasi and Zhuang, 2020) (a relatively shallow pre-training approach based on FastText) for encoding text, and reported the best performance of macro-F1 28%. The models reported in this paper outperform the best result reported in (Paul et al., 2022) massively on the ILSI dataset (Table 3). We think that transformer-based pre-training has helped greatly on this task. We also think that some fine-tuning experimental setups, such as different initial learning rates to different kinds of layers, have helped to optimize the models effectively.

On the other hand, Chalkidis et al. (2022) used a very similar architecture to ours for the ECTHR-B dataset, i.e., HierBERT, but with a 2-layer transformer on top instead of LSTM. They also reported results using LegalBERT and CaseLawBERT encoders (m-F1 of 74.7% and 70.3% respectively), which we beat with our architecture (Table 3). We also experimented with this version of the HierBERT architecture (with a 2-layer transformer on top) for both datasets, and we observed that the performance was slightly less on ECTHR-B and significantly less on ILSI as compared to the HierBERT version with LSTM + Attn on top. Thus, we only report the results for HierBERT with LSTM + Attn on top. Our model with InLegalBERT obtains higher performance over all results reported in Chalkidis et al. (2022) for ECTHR-B – the macro-F1 obtained by our model is 75.88% compared to the best value of 74.7% reported in Chalkidis et al. (2022).

5.2 Semantic Segmentation of case judgements

Legal case judgements are composed of different functional or rhetorical segments such as Facts, Issue, Ratio for the ruling, Ruling, etc. (Bhattacharya et al., 2019b). Demarcating these segments can be helpful, since many applications require analyzing some specific segments while not considering the rest, e.g., we need to extract only the facts for tasks such as LSI. Again, since legal case judgements are very long, law professionals may want to read only certain segments such as only the legal issues in a case. Legal judgements in many countries do not have clearly demarcated boundaries for the above segments, and thus automated methods for semantic/rhetorical segmentation can greatly help in these practical applications.

Semantic/rhetorical segmentation of legal case judgements has also been a very widely researched task. A number of methods have been applied starting from legacy Machine Learning Models such as Conditional Random Fields (CRFs) (Lafferty et al., 2001) with handcrafted features. Modern deep learning techniques have replaced handcrafted features with automatic features extracted using neural networks (Bhattacharya et al., 2019b, 2021). The task can be considered as a sequence labeling problem, where the entire document can be considered as a sequence of sentences which have different respective labels.

5.2.1 Datasets

We use two datasets for this task as well:

(i) ISS: We use the dataset provided by Bhattacharya et al. (2019b) and call it the Indian Semantic Segmentation dataset (ISS). The ISS dataset has 50 documents from the Supreme Court of India, with each document segmented into sentences, and each sentence marked with one of seven semantic/rhetorical segment labels – Facts, Arguments, Statutes, Precedents, Ratio Decidendi, Ruling by Lower Court and Ruling by Present Court. In total, there are 9,308 sentences labeled with one of the segment labels stated above.

(ii) UKSS: We also use the dataset based on UK Supreme Court cases provided by Bhattacharya et al. (2021), calling it the UK Semantic Segmentation dataset (UKSS). The UKSS dataset has 50 documents from the Supreme Court of the UK, segmented into sentences and annotated with one of the same seven semantic/rhetorical as the ISS dataset. This dataset contains a total of 18,155 sentences each labeled with one of the seven segment labels stated above.
## 5.2.2 Models

We use the HierBERT-CRF architecture for this task. This is simply the HierBERT architecture, minus the final attention layer, and with a CRF (Lafferty et al., 2001) head on top. CRFs can be useful for extracting relationships from the gold-standard sequence of labels during training.

After encoding each sentence with the lower-level encoder, we pass the [CLS] representations through an LSTM layer to obtain contextualized sentence representations. These are then passed through a fully connected layer with CRF layer on top. We used the Negative Log-Likelihood for training and Macro-F1 for evaluation.

We limit the sentence length to 128 tokens, but we have to include all sentences of a document since each is associated with a label. All intermediate embeddings (for LSTM encoder, etc.) are of 768 dimensionality. We use an effective batch size of 2 documents and train for 20 epochs. Different initial learning rates are set for different layers (5e-3 for topmost FC + CRF layer, 1e-3 for intermediate LSTM layer and 1e-5 for the lowermost BERT layers).

We run 5 variations of the architecture described above, with the lower-level encoder of each version comprising of one of the PLMs discussed earlier (BERT, LegalBERT, CaseLawBERT, InLegalBERT and InCaseLawBERT). Apart from the lower-level encoder, all the 5 variations are identical in all other aspects. We also keep the same settings for both datasets.

### 5.2.3 Results

Since both the datasets for this task are quite small, we use 5-fold cross-validation to obtain a better performance measure. The average results (across 5 folds) for the Semantic Segmentation task on both ISS and UKSS datasets are shown in Table 4.

For this task, the trends are very similar for both datasets. Taken off-the-shelf, both LegalBERT and CaseLawBERT obtain gains over BERT in terms of F1 score across both datasets, however the difference is larger for ISS than UKSS. LegalBERT does better than CaseLawBERT for the UK dataset and vice-versa for the Indian dataset (see Table 4). This observation is similar to what we observed in the LSI task as well (see Section 5.1).

On further re-training on Indian data, performance of both LegalBERT and CaseLawBERT increases, however the margins are lesser for CaseLawBERT on both datasets. InLegalBERT beats all variants in terms of macro-F1 on both datasets.

### Comparison with the original works:

None of the transformer-based models stated above are able to perform as well as the best method in (Bhattacharya et al., 2019b) for the ISS dataset, which has the same broad architecture as described above, but uses a Sent2vec encoder (Moghadasi and Zhuang, 2020) (based on FastText) trained on Indian Supreme Court documents instead. This Sent2vec-based model has a very high performance across all metrics (> 80% m-F1) as reported in (Bhattacharya et al., 2019b). We are yet to understand how this relatively shallow model performs so much better compared to transformer-based models for the ISS dataset, but we suspect this could be due to the very small size of the ISS dataset (which may not be sufficient to fine-tune transformer-based models effectively). We plan to explore this in more detail in our future studies.

For the UKSS dataset, Bhattacharya et al. (2021) fine-tuned both BERT and LegalBERT under the same HierBERT-CRF setup as we are using, but had frozen all but the top 2 layers of BERT. Under our setup (fine-tuning all layers), we achieve similar performance as compared to the result reported by Bhattacharya et al. (2021) for LegalBERT encoder, which is 60% m-F1 (see Table 4). Using In-

### Table 4: Performance over the ISS and UKSS datasets for Semantic Segmentation task. All reported values are macro-averaged and then averaged across 5-folds (cross-validation) and in terms of percentage.

| Encoder Module   | ISS dataset |          |          | UKSS dataset |          |          |
|------------------|-------------|----------|----------|--------------|----------|----------|
|                  | mP         | mR       | mF1      | mP           | mR       | mF1      |
| BERT             | 67.56      | 64.21    | 64.41    | 64.28        | 58.51    | 59.54    |
| LegalBERT        | 71.81      | 65.70    | 67.32    | 62.87        | 60.22    | 60.03    |
| CaseLawBERT      | 70.39      | 68.53    | 68.03    | 61.61        | 60.23    | 59.68    |
| InLegalBERT      | 71.65      | 68.36    | **68.98**| 63.93        | **60.95**| **61.54**|
| InCaseLawBERT    | **72.20**  | 68.21    | 68.80    | **64.68**    | 59.82    | 60.85    |
LegalBERT further improves on this performance to achieve 61.54% m-F1 which is higher than the best result reported in Bhattacharya et al. (2021).

5.3 Court Judgment Prediction

As discussed in Section 5.1, automatically predicting the outcome of court cases has been widely studied in recent years (Zhong et al., 2020). This has mostly been done via the task of Legal Judgment Prediction (LJP), where, given the facts of a case, we are to predict the laws/statutes violated, applicable charges and terms of penalty.

Along these lines, the CJPE (Court Judgement Prediction and Explanation) task, introduced by Malik et al. (2021), is to predict the final decision of the court, based on the rest of the case judgement (i.e., the input is the case judgement document with the final decision removed). In the Indian scenario, a court case usually consists of one or multiple appeals/claims filed by the appellant against the respondent, and the judge needs to provide an ‘accept’ or ‘reject’ decision for each of these claims. Thus, this can be modeled as a binary text classification task.

5.3.1 Dataset

The ILDC family of datasets, introduced by Malik et al. (2021), contain two different types of training data. The ILDC-single dataset consists of approx. 7.6K Supreme Court of India case documents that have a single claim/appeal (and thereby a single accept/reject decision for the same) or multiple appeals, but the decisions are the same across all those appeals. The ILDC-multi dataset is a superset of ILDC-single, and consists of approx. 35K Supreme Court of India case documents each having multiple claims/appeals; a single label is assigned for each document – ‘accept’ if at least one appeal in that case document is accepted, ‘reject’ otherwise. For our current experiment, we consider the ILDC-multi dataset.

5.3.2 Model

We use the HierBERT architecture which was also used by Malik et al. (2021) for their results. The entire text of a document is chunked into groups of 128 tokens, and passed to the HierBERT model. The [CLS] token embeddings are passed to a higher-level LSTM + Attn encoder to get a single representation for the entire document. This representation is then passed to a fully connected layer with 1 output unit and sigmoid activation. Binary Cross Entropy Loss is used for training.

As stated earlier, the HierBERT architecture has a lower-level encoder. We run 5 variations of the architecture described above, with the lower-level encoder of each version comprising of one of the PLMs (BERT, LegalBERT, CaseLawBERT, InLegalBERT and InCaseLawBERT). Apart from the lower-level encoder, all the 5 variations are identical in all other aspects.

5.3.3 Results

We report macro-Precision, macro-Recall and macro-F1 metrics for evaluating the different PLMs. The trends for this task are also similar to that in the Semantic Segmentation task (see Table 5). LegalBERT improves massively over BERT, while there is a smaller but significant improvement achieved by injecting India-specific behaviour in InLegalBERT (macro-F1 of 83.09 % as compared to 78.21 % for LegalBERT). Similarly, CaseLawBERT does better than LegalBERT taken off-the-shelf, but its re-trained variant (over Indian legal text) InCaseLawBERT falls short of InLegalBERT. The InLegalBERT model attains the highest values in terms of all metrics Precision, Recall and F1, across all models.

Comparison with the original work: The best results for the judgement prediction task reported in Malik et al. (2021) was macro-F1 77.79% which was obtained via the same hierarchical architecture (as stated above) but employing XLNet and BiGRU as the encoding module. The InLegalBERT and InCaseLawBERT models developed in this work have achieved substantially higher performances.

| Encoder Module | mP  | mR  | mF1  |
|----------------|-----|-----|------|
| BERT           | 71.31 | 70.98 | 71.14 |
| LegalBERT      | 79.85 | 78.49 | 78.21 |
| CaseLawBERT    | 82.62 | 82.42 | 82.38 |
| InLegalBERT    | 83.43 | 83.15 | 83.09 |
| InCaseLawBERT  | 83.05 | 82.82 | 82.77 |

Table 5: Performance over the ILDC-multi dataset for the Court Judgement Prediction (CJPE) task. All reported values are in terms of percentage.
than the best result reported in Malik et al. (2021) (Table 5).

6 Conclusion and Future Work

In this work, we have investigated the gains of re-training existing pre-trained models for the legal domain, namely, LegalBERT (Chalkidis et al., 2020) and CaseLawBERT (Zheng et al., 2021), on a large corpus of Indian legal data. Based on the results across three practically important legal NLP tasks over standard datasets from India as well as from other domains/countries — Legal Statute Identification, Semantic Segmentation, and Court Judgement Prediction — we can conclude that further pre-training on Indian legal text helps, in general, to improve the performances for both the above models.

We observe some common trends about various PLMs in the legal domain:
(i) LegalBERT improves massively over the standard BERT across all tasks in the legal domain, and CaseLawBERT does even better than LegalBERT over the tasks on the Indian datasets. However, for the datasets from the European courts, LegalBERT does better than CaseLawBERT. This probably is related to the fact that LegalBERT has been trained on documents from both the UC and ECtHR, while CaseLawBERT has been trained solely on US data.
(ii) When re-trained on Indian data, InLegalBERT improves significantly over LegalBERT, while the gains are much smaller for InCaseLawBERT over CaseLawBERT for Indian datasets. In fact, InLegalBERT attains the best F1 scores across all the three tasks and five datasets that we experimented with, which shows that the LegalBERT model is more adaptable to re-training on new data, as compared to the CaseLawBERT model.
(iii) InLegalBERT not only outperforms other legal PLMs in terms of macro-F1 for Indian datasets, but for datasets from other countries as well. We can reasonably conclude that re-training on Indian data has helped the model improve in legal NLP tasks across domains/countries.

We make the PLMs InLegalBERT and InCaseLawBERT available publicly to the research community. These models have already obtained better results than those originally reported for two important benchmark tasks over Indian legal text – the LSI task over the ILSI dataset (Paul et al., 2022), and the CJPE task over the ILDC dataset (Malik et al., 2021). The InLegalBERT model also improves across two benchmarks over non-Indian legal text — the LSI task over the ECtHR-B dataset (Chalkidis et al., 2022) and the Semantic Segmentation task over the UKSS dataset (Bhattacharya et al., 2021). Given that the number of NLP studies on legal text is increasing rapidly in recent years, we hope that these LMs will benefit other researchers working on Legal NLP.

In future, we plan to further investigate the effects of introducing a custom vocabulary suited for Indian legal data, and pre-training a BERT-base model from scratch over our data using the customized vocabulary.

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