LegalEval: Understanding Legal Texts
NLP Course Project & Project Work

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Abstract

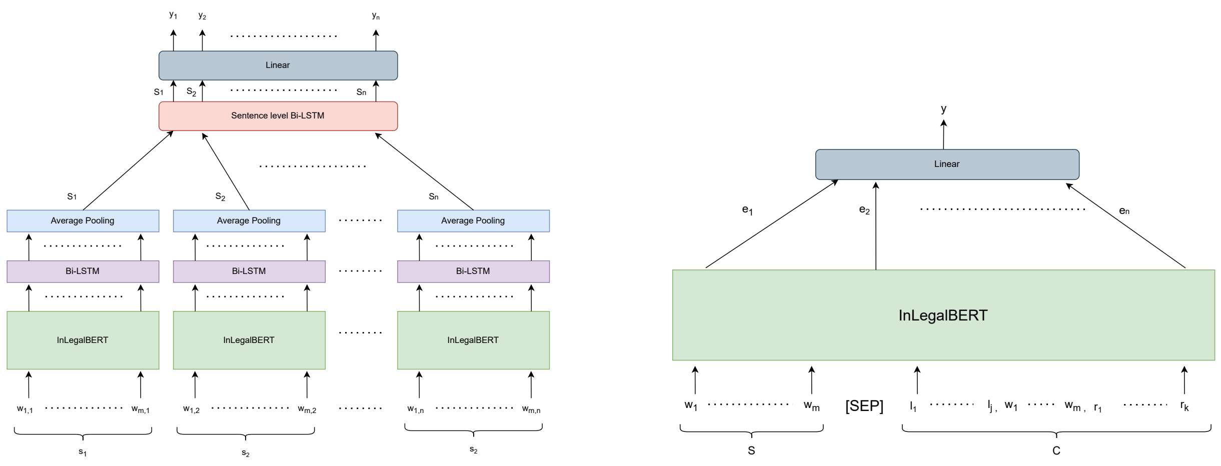
This study aims to tackle some challenges posed by legal texts in the field of NLP. The LegalEval challenge[1] proposes three tasks, based on Indial Legal documents: Rhetorical Roles Prediction, Legal Named Entity Recognition, and Court Judgement Prediction with Explanation. Our work focuses on the first two tasks. For the first task we present a context-aware approach to enhance sentence information. With the help of this approach, the classification model utilizing InLegalBert as a transformer achieved 81.12% Micro-F1. For the second task we present a NER approach to extract and classify entities like names of petitioner, respondent, court or statute of a given document. The model utilizing XLNet as transformer and a dependency parser on top achieved 87.43% Macro-F1.

Task A - Rhetorical Roles Prediction

A.1 Introduction

The exponential growth of pending legal cases in highly populated countries, such as India, has highlighted the need for automation in the judicial process. Although a full automation of the legal domain may not be feasible, intermediate tasks can be automated to assist legal practitioners and improve efficiency. Nevertheless, the unique nature of legal texts presents challenges for direct application of NLP models and techniques developed for common texts, thus requiring the development of specialized NLP approaches specifically tailored to the legal domain.
The objective of this first task is to segment a given legal document by predicting the rhetorical role label for each sentence such as a preamble, fact, ratio, arguments, etc. These are referred to as **Rhetorical Roles (RR)**. This segmentation is a fundamental **building block** for many legal AI applications like judgment summarizing, judgment outcome prediction, precedent search, etc.
Legal documents are typically long (tens of pages), unstructured, noisy (e.g., grammatical and spelling mistakes due to manual typing in courts), and use different lexicon (legal jargon), which makes end-to-end transformer-based pre-trained models for sentence classification ineffective. The legal domain has several sub-domains (corresponding to different laws, e.g., criminal law, income tax law) within it. Although some of the fundamental legal principles are common, the overlap between different sub-domains is low; hence systems developed on one law (e.g., income tax law) may not directly work for another law (e.g., criminal law), so there is the problem of a domain shift.
In this paper we propose an approach based on the usage of transformer-based models pre-trained on legal text and fine-tuned on a Rhetorical Roles dataset in a **context aware** way, to make them able to accurately segment even long documents. We first experimented with simple single sentence classification transformers (both pre-trained on general texts and legal texts) and then, leveraging on the fact that in a document nearby sentences classes tend to influence each other, we experimented enriching the sentence representations with information coming from the context. First attaching 2 BiLSTM layers to the transformer embedding model and then simply extending the input tokens of the trasformer by adding the tokens from a context window around the sentence. With the baseline models and the one with BiLSTM we reached around **67%** of Micro-F1, we managed to obtain an increase of 10 points with our context based models, reaching **82%** on the test set.
All the experiments have been conducted on the dataset provided by the challenge [8]. Only the best model was trained on the whole dataset (including the test set) in order to produce the best re-

[1] `https://sites.google.com/view/legaleval/home`



(a) **M0**: InLegalBERT + 2 BiLSTM

(b) **M2**: Context aware InLegalBERT

Figure 1: Architectures

sults possible for the challenge's submission. With this retraining procedure, the context aware model using InLegalBERT reached a Micro-F1 score of **81.12%** on the submission data.

A.2 System description

In this task the usual pipeline of an NLP task was followed. During the preprocessing step we focused on the creation of the context's window for each sentence. Starting from the position of the sentence in the document we considered a context window of varying size, such that each time the total number of tokens of the sentence plus the context would not exceed the maximum sequence length of the transformer (usually 512). The context created in this way was then used only in the aforementioned context aware models.
At a first glance, the Rhetorical Role segmentation task can be seen as a simple text classification problem in which we have to classify each sentence of a document as belonging to one of the Rhetorical Role classes, independently of each other. For this reason we first selected the standard versions of **BERT** [4] and **RoBERTa** [11] as baselines to be tested in their sentence classification setting. In this models a transformer architecture produces the embedding of the sentence, which is then processed through a dropout layer and a linear classifier.
Drawing inspiration from [12], we leveraged on the fact that sentences in legal judgements documents follow a tight structure and do not abruptly change RR, indeed the text tends to maintain a topical coherence. Hence, we propose a solution that enables reasoning on the context of the sentences when classifying.
We considered a model that utilizes a pre-trained BERT embedding module. The module is then followed by the integration of two Bi-LSTM layers and a linear classifier, with an average pooling operation performed at token level between the two LSTM layers. We then evaluated two models with the same architecture as the baselines, utilizing pre-trained transformers, Legal-RoBERTa [2] (trained on legal documents) and InLegalBert [14], which was trained on Indian legal documents. These models were fed with the target sentence and its surrounding context to enable the BERT modules to generate contextually enriched sentence embeddings, which were then fed into a linear classifier to output classes predictions.
The following naming convention will be used from now on to refer to the described models:

- **B1** : Single sentence BERT
- **B2** : Single sentence RoBERTa
- **M0** : Single sentence InLegalBERT + 2 BiLSTM
- **M1** : Context aware Legal-RoBERTa
- **M2** : Context aware InLegalBERT

A.3 Data

The dataset used in this task is the **Corpus for Automatic Structuring of Legal Documents**[8]. This dataset contain a corpus of 40,305 sentences

[2]https://huggingface.co/saibo/legal-roberta-base.

annotated with 12 different RRs, as one can see in Table 1. For the purpose of the challenge, smaller annotated datasets were released, divided into a training and a development set of size 28,986 and 2,878, in order to make training and evaluation processes easier. A non-annotated test dataset was also released during the submission phase of the task, and was used to compute the metrics and build a leaderboard. The definitions of the RRs are the following, plus a NONE label to identify neutral sentences that do not belong to any RR:

- **Preamble (PREAMBLE):** Meta data related to the legal judgement document.
- **Facts (FAC):** This corresponds to the facts of the case. It refers to the chronology of events that led to filing the case and how it evolved.
- **Ruling by Lower Court (RLC):** A lower court's verdict, analysis, and the ratio behind the judgment by a lower court is annotated with this label.
- **Issues (ISSUE):** The key points on which the verdict needs to be delivered.
- **Argument by Petitioner (ARG_PETITIONER):** Precedent cases argued by petitioner lawyers fall under this category.
- **Argument by Respondent (ARG_RESPONDENT):** Precedent cases argued by respondent lawyers fall under this category.
- **Analysis (ANALYSIS):** Discussions on how the law is applicable or not applicable to the current case.
- **Statute (STA):** Texts in which the court discusses established laws, e.g. Acts, Sections, Articles, Rules, Order, Notices, Notifications etc.
- **Precedent Relied (PRE_RELIED):** Texts in which the court discusses prior case documents, discussions and decisions which were relied upon by the court for final decisions.
- **Precedent Not Relied (PRE_NOT_RELIED):** Texts in which the court discusses prior case documents, discussions and decisions which were not relied upon by the court for final decisions.
- **Ratio of the decision (RATIO):** Texts including the main reason given for the application of any legal principle to the legal issue. It is the result of the analysis by the court.
- **Ruling by Present Court (RPC):** Final decision + conclusion + order of the Court following from the natural/logical outcome of the rationale.
- **NONE:** If a sentence does not belong to any of the above categories, it is labeled as NONE.

Class	**Count**
ANALYSIS	14300
ARG_PETITIONER	1771
ARG_RESPONDENT	1068
FAC	8045
ISSUE	535
NONE	2037
PREAMBLE	6116
PRE_NOT_RELIED	217
PRE_RELIED	1934
RATIO	1014
RLC	1081
RPC	1562
STA	625
TOTAL	**40305**

Table 1: Corpus for Automatic Structuring of Legal Documents

As we can see from Table 1 the class distribution in the corpus is highly imbalanced, reflecting the inherent imbalance in legal documents. These documents consist of long discussions and analysis sections, along with short and standardized formulas for preambles and final judgements. Hence, balancing the class distribution is not a straightforward task.

A.4 Experimental setup and results

The experiments of this work were performed on the five aforementioned models. As previously stated, only two annotated datasets were released for this challenge: a training set and a development set. In order to properly test and compare our models we further split the training set into a training and a validation set, while keeping the development set as a test set to compare the generalisation capabilities of our models. We used the validation set to perform hyperparameter tuning for all models and then compared the results on the test set of the different models. The models were implemented using the PyTorch framework, through the use of `AutoModelForSequenceClassification` class of the HuggingFace library, that allows to load different transformer models with a linear layer on top. With regards to **M0**, we re-defined the model classes from HuggingFace by adding the BiLSTM between the transformer and the linear classifier. All the models were trained and evaluated using the HuggingFace `Trainer`[3] API to guarantee correctness and reproducibility of the results. AdamW was chosen as optimizer for all the models, as it is the standard choice in literature for fine-tuning transformer models, with a learning rate of 2×10^{-5}. Furthermore, to perform regularization and prevent overfitting an early stopping callback and a label smoothing factor of 0.2 were added to the training recipe, with the only exception of model **M0** whose performance decreased with label smoothing. The baselines and model **M0** have been trained with a higher batch size (128) in order to speed up a bit the training process. Unfortunately this wasn't possible with the context aware models, since their larger input size combined with large batch sizes exceeded the GPU memory provided by Google Colab. All the experiments have been conducted on Google Colab with free plan.

Parameter	**Value**
epochs	3
batch size	16
learning rate	2×10^{-5}
optimizer	AdamW
scheduler	linear
weight decay	0.01
label smoothing	0.02
precision	16-bit

Table 2: Key training procedure parameters

[3] `https://huggingface.co/docs/transformers/main_classes/trainer`.

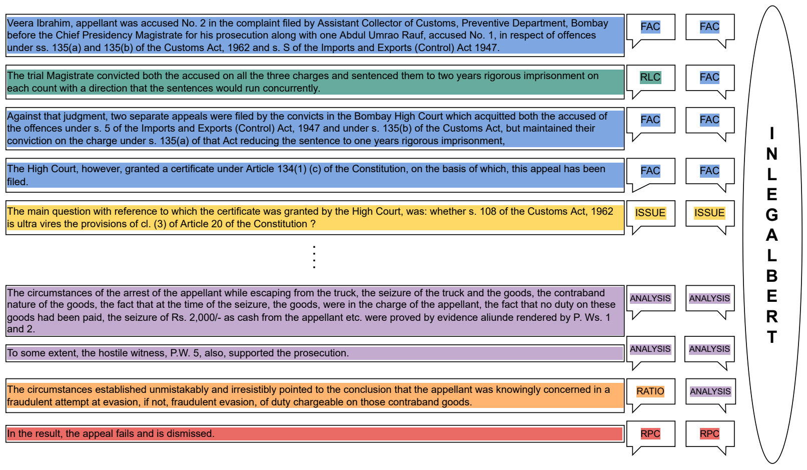
The results obtained on the validation and test set are shown in Table 3. We used the F1 score micro average (which coincides with accuracy in this multiclass setting) as the main metric, since it is the one that determined the challenge leaderboard. It is clear that InLegalBERT (**M2**) outperforms the other models across all metrics. The baseline models **B1** and **B2** reached Micro-F1 scores of 65% and 72% respectively, with **M0** performing slighlty worse. On the other hand, the use of context-aware models (**M1** and **M2**) results in a 10% improvement in Micro F1, reaching Micro-F1 scores of 80% and 82% respectively.
To submit our results and participate in the challenge, **M2** was then retrained using all the available annotated data (the union of the training and the development set) in order to be sure to maximize performances. The model obtained a Micro-F1 score of 81.12% on the submission data, that resulted in the 8th position in the leaderboard.

A.5 Discussion

Looking at the results in Table 3 we can see that the context aware models clearly outperform the baseline models, since they leverage on context enriched sentence embeddings to perform predictions. The introduction of the context as input enabled the model to gather more information from the semantic meaning of the surrounding sentences, that resulted in more effective sentence embeddings when predicting the Rhetorical Role. Model **M0**, instead, reported similar scores with respect to the baselines, probably due to the fact that the enrichment that a sentence embedding receives comes only from the sentences in the same batch, which are not necessarily equally distributed around the sentence.
On the other hand, adding context passages to the input drastically increases the input size of the model to its maximum, which directly affects performances in terms of longer training and infer-

Model	**Validation Set**			**Test Set**		
	Weighted Precision	**Weighted Recall**	**Micro F1**	**Weighted Precision**	**Weighted Recall**	**Micro F1**
B1	63.0	65.0	65.0	64.0	65.0	65.0
B2	67.0	69.0	69.0	72.0	72.0	72.0
M0	56.0	63.0	63.0	60.0	65.0	65.0
M1	77.0	76.0	76.0	79.0	80.0	80.0
M2	**77.0**	**77.0**	**78.0**	**81.0**	**82.0**	**82.0**

Table 3: Performance on validation and test set


Veera Ibrahim, appellant was accused No. 2 in the complaint filed by Assistant Collector of Customs, Preventive Department, Bombay before the Chief Presidency Magistrate for his prosecution along with one Abdul Umrao Rauf, accused No. 1, in respect of offences under ss. 135(a) and 135(b) of the Customs Act, 1962 and s. S of the Imports and Exports (Control) Act 1947.

The trial Magistrate convicted both the accused on all the three charges and sentenced them to two years rigorous imprisonment on each count with a direction that the sentences would run concurrently.

Against that judgment, two separate appeals were filed by the convicts in the Bombay High Court which acquitted both the accused of the offences under s. 5 of the Imports and Exports (Control) Act, 1947 and under s. 135(b) of the Customs Act, but maintained their conviction on the charge under s. 135(a) of that Act reducing the sentence to one years rigorous imprisonment,

The High Court, however, granted a certificate under Article 134(1) (c) of the Constitution, on the basis of which, this appeal has been filed.

The main question with reference to which the certificate was granted by the High Court, was: whether s. 108 of the Customs Act, 1962 is ultra vires the provisions of cl. (3) of Article 20 of the Constitution ?

⋮

The circumstances of the arrest of the appellant while escaping from the truck, the seizure of the truck and the goods, the contraband nature of the goods, the fact that at the time of the seizure, the goods, were in the charge of the appellant, the fact that no duty on these goods had been paid, the seizure of Rs. 2,000/- as cash from the appellant etc. were proved by evidence aliunde rendered by P. Ws. 1 and 2.

To some extent, the hostile witness, P.W. 5, also, supported the prosecution.

The circumstances established unmistakably and irresistibly pointed to the conclusion that the appellant was knowingly concerned in a fraudulent attempt at evasion, if not, fraudulent evasion, of duty chargeable on those contraband goods.

In the result, the appeal fails and is dismissed.

Figure 2: Example of a segmented document

ence times. Nonetheless, in a practical use case, when processing a document this operation will be performed just once at the beginning of a longer pipeline. Among the two context aware models the best one resulted to be the one using InLegalBERT, which is referable to the fact that it has a better understanding of the specific jargon used in indian legal documents, which it was pre-trained on.

Class	Precision	Recall	F1	Support
PREAMBLE	98.0	100.0	99.0	507
NONE	96.0	86.0	91.0	190
FAC	81.0	89.0	85.0	581
ARG_RESPONDENT	64.0	74.0	68.0	38
RLC	66.0	27.0	38.0	116
ARG_PETITIONER	57.0	18.0	28.0	65
ANALYSIS	78.0	90.0	84.0	985
PRE_RELIED	74.0	44.0	55.0	142
RATIO	70.0	37.0	48.0	71
RPC	83.0	92.0	88.0	92
ISSUE	66.0	78.0	71.0	51
STA	50.0	68.0	58.0	28
PRE_NOT_RELIED	0.0	0.0	0.0	12
Weighted	**81.0**	**82.0**	**81.0**	**2878**

Table 4: **M2** - Classification report on the test set

Analysing the predictions and the errors of this model we encountered the same trends reported in [9]. From the classification report in Table 4 we can see that PREAMBLE sentences are almost perfectly classified, probably due to the fact that they almost always include proper nouns, repeated formulas, dates and other highly recognizable patterns. Some other classes like FAC, NONE, ANALYSIS and RPC reach high F1-score values. It is important to note that in the RPC (Ruling by Present Court) class the model has a recall of 92%, meaning that it correctly identifies the final judgement of the court in most of the cases (even if it has a small support in the dataset). On the other hand the model performs no predictions for the class PRE_NOT_RELIED, probably due to the very small support in the dataset. Examining the precision and recall scores for the majority class (ANALYSIS), it can be concluded that the model tends to default to this class when uncertain. This has resulted in significant misclassification for classes with low recall scores, with the exception of RLC, which was more frequently misclassified as FAC, as also happened to human dataset annotators [9]. This behaviour is probably related to the fact that sentences belonging to the core section of a document of classes PRECEDENT, ANALYSIS and ARGUMENTS all contain discussions of the court or statements from the parts, which only differ for the subject of the discussion (whether it is a precedent case or not) or for the part that is speaking (whether it is the petitioner or the respondent).
A potential solution to the problem at hand is the use of a multilabel setup, which would allow the model to predict multiple classes for each sample. With this approach, if the model predicts the majority class, further investigation can be conducted on the other predicted classes to improve or correct the prediction.
Examining the output example in Figure 2, it is clear that InLegalBert performs well overall. However, it may struggle in predicting the rhetorical role of a sentence if the surrounding context has a different Rhetorical Role. Additionally, it can be observed that sentences labelled with less frequent labels, such as RATIO, are often misclassified as the majority class, ANALYSIS. This tendency of the model to default to the majority class label highlights the need for further improvement.

Task B - Legal Named Entity Recognition

B.1 Introduction

Extracting legal named entities from court judgment texts allows to effectively generate metadata information that can be exploited for many legal applications like knowledge graph creation, co-reference resolution and in general to build any query-able knowledge base that would allow faster information retrieval.

To address this domain-specific NER task, we've experimented two transformers-based approaches with increasing model complexity, trying to reproduce both the baseline's methods proposed by P.Kalamkar et al.[7].

The **first method**, consisting of a simple linear layer as a head and fine-tuning of the entire model, was easily reproducible. We were also able to achieve a higher score. For the **second one**, which uses a transition-based dependency parser, we tried to reproduce it stacking on top of the transformer a BiLSTM and a CRF layer as in [10][3] and in particular as in the work of R.Yan et al.[17]. However, in this case we were not able to reach the same performance.

From now on, we'll refer to the first (simple) model as the **baseline model** (BM) and to the variant with BiLSTM and CRF as **custom model** (CM). We experimented different transformers, namely **RoBERTa**, **InLegalBERT** and **XLNet**, given its ability to process longer sequences of tokens. After having tested all of them for the baseline model, the best performing ones (RoBERTa and XLNet) were then used as base for our custom models. All the experiments have been conducted on the dataset provided by the challenge [7]. Only the best models were trained on the whole dataset (including the validation set) in order to produce the best results possible for the challenge's submission. Our best baseline and custom models reached respectively **86,04%** and **87,4% F1 Score**, surpassing the first method proposed in [7] by 5,0%.

B.2 Background

As reported in the original paper, the authors of the challenge obtained their best performance by stacking a **transition-based dependency parser** [6] on top of the transformer. A dependency parser captures the dependencies between the tokens of a sentence in order to determine its grammatical structure and the direct relationships between them. In the proposed model [7] was used the implementation `DependencyParser`[4] of spacy. Since there is not a PyTorch implementation of this class, we decided to use a **Conditional Random Field** layer as dependency parser, as suggested in different papers [2]. A CRF can easily capture the relationships between tokens using a probabilistic model based on the Viterbi algorithm [5]. For example, it enforces the rule that a token labeled as I-COURT must always follow a B-COURT token, and cannot follow an O label.

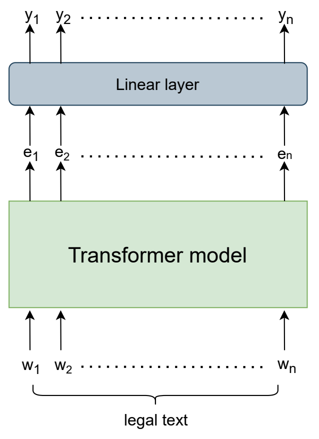
B.3 System description

Unlike many NER applications, where the input text is already in a processed form, our system was designed to handle raw text and perform end-to-end named entity recognition, preserving the original text format. Therefore, no text cleaning was performed (except for RoBERTa, see B.4 Data), and labels were mapped from words to tokens using the **B-I-O** labeling format [16]. The code for transforming our raw data to a dataset format is an heavy adaptation of the one proposed by S.Subedi[18]. Furthermore, given the limited amount of tokens that a transformer can process and the fact that some texts in our dataset were too long (1.44% of samples exceed 512 tokens, with a peak of 5000), we developed a **sliding window** approach, for both the training and inference steps, that allowed us to avoid input truncation.

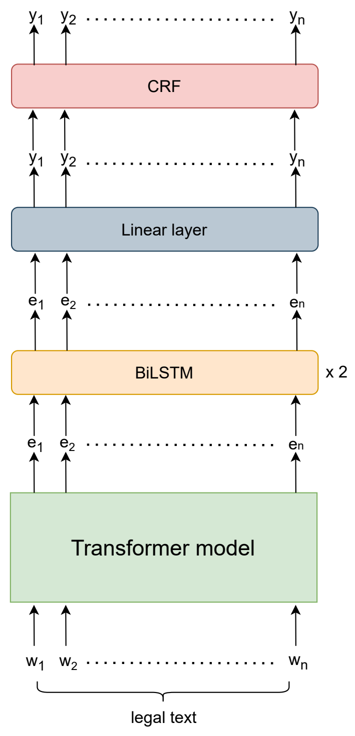
The sliding window for the training procedure is triggered only if the text provided is longer than the maximum length processable by the transformer; in this case the window will have size equal to the maximum length and it will move with a **stride** that is half of the window size. We use this stride to prevent entities from being cut by the sliding window, ensuring their full appearance at least once. At inference time, the code for the sliding window approach is an adaptation of [13]. It processes the texts as described above; hence the label assigned to an entity is the one with maximum of the average of the scores given by the inference on each sliding window.

For the baseline architecture, following [7], we used the standard token classification model, so a simple fully connected layer on top of a transformer model (Figure 3a).

[4]`https://spacy.io/api/dependencyparser`



(a) **BM**: Transformer + Linear classifier



(b) **CM**: Transformer + BiLSTM + CRF

Figure 3: Architectures of NER models

The model experimented were:

- **BM1** : RoBERTa [11]
- **BM2** : InLegalBERT [14]
- **BM3** : XLNet [19]

XLNet, contrarily to the first two, can process inputs of any dimension, nonetheless we used 1024 tokens as we were restricted by memory limitations.
Regarding the custom models, we mainly experimented two variants using the best performing transformer in the baseline models:

- **CM1** : RoBERTa - BiLSTM - CRF [3]
- **CM2** : XLNet - BiLSTM - CRF [17][3]

They share the same structure, differing only for the transformer backbone: two BiLSTM layers, with a dropout (rate 0.5) between them, and a fully connected layer with a CRF on top (Figure 3b). Other variants using either BiLSTM or CRF were tested but with no notable results.

B.4 Data

The dataset used in this task is the **Legal Named Entity Recognition Corpus** (more details in [7]). This dataset contains a corpus of 16,570 sentences extracted from Indian court judgements [1] and annotated with 14 entities and roles (described in [15]). Sentences can represent either the preamble or a judgement sentence of a court judgement, so different sentences may belong to the same court document.
For the purpose of the challenge, a smaller annotated dataset was released. It is divided into a training and a development set of size 10,995 and 1,074, in order to make training and evaluation processes easier. Typically preambles are larger than judgements and they contain more entities. Some entities are present only in the preamble, others only in the judgment text and some in both. Nevertheless, preambles and judgments are treated in the same way, since when we perform inference there is no distinction between them. The dataset conversion to B-I-O format is implemented using a sliding-window approach, since multiple sequences exceed the maximum limit of the tokenizers. The pre-processing step involved in this study was limited to the elimination of multiple white spaces in

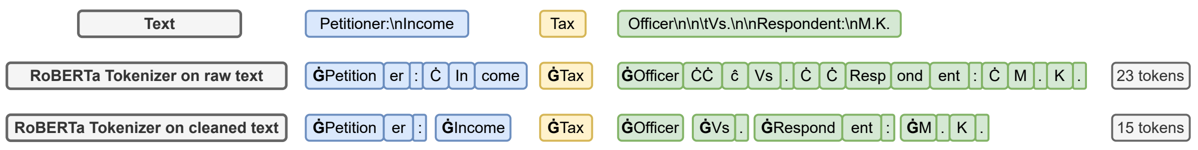

Text
Petitioner:\nIncome
Tax
Officer\n\n\tVs.\n\nRespondent:\nM.K.
RoBERTa Tokenizer on raw text
ĠPetition | er | : | Ċ | In | come
ĠTax
ĠOfficer | ĊĊ | ĉ | Vs | . | Ċ | Ċ | Resp | ond | ent | : | Ċ | M | . | K | .
23 tokens
RoBERTa Tokenizer on cleaned text
ĠPetition | er | :
ĠIncome
ĠTax
ĠOfficer
ĠVs | .
ĠRespond | ent | :
ĠM | . | K | .
15 tokens

Figure 4: Comparison of tokenization on raw and cleaned sentence

Named Entity	**Found in**	**Count**	**Avg.Words**
PRECEDENT	Judgment	1351	10
COURT	Both	2367	7
CASE_NUMBER	Judgment	1040	4
RESPONDENT	Both	3862	4
PETITIONER	Both	3068	3
LAWYER	Preamble	3505	2
STATUTE	Judgment	1804	2
PROVISION	Judgment	2384	2
ORG	Judgment	1441	2
DATE	Judgment	1885	1
GPE	Judgment	1398	1
WITNESS	Judgment	881	1
OTHER_PERSON	Judgment	2653	1
JUDGE	Both	2325	1
TOTAL		**29964**	

Table 5: Legal Named Entities Recognition Corpus

sentences and it was only performed for experiments utilizing RoBERTa models. The motivation is that only RoBERTa tokenizer considers as token multiple spaces, hence if a sentence contains a lot of white spaces the length of the meaningful context is drastically reduced. XLNet and BERT-like tokenizers, instead, do not tokenize white spaces, so removing them will be useless for these models. In Figure 4 is reported the tokenization of a sentence with RoBERTa before and after the preprocessing. We can observe that the tokenizer first encodes the newline character as "Ċ" and the tab character as "ĉ". If we then remove the multiple spaces, the number of tokens is reduced. We have decided not to remove punctuation and to use only case-sensitive models, since many entities contain periods and commas and the capitalization could be a hint for entities like organizations, judges, petitioners and others.

B.5 Experimental setup and results

Given the constraints on the number of submissions permitted by the challenge, the decision was made to split the training set by using 10% of the training samples as a validation set and utilizing the provided development set as the test set. The results presented in the subsequent section reflect this configuration. For the final submission, all the available data was utilized for training without conducting evaluation.

The models were implemented using the PyTorch framework, in particular for the baseline model we used the `AutoModelForTokenClassification` class of the HuggingFace library, that allows to load different transformer models with a linear layer on top. Instead, for our custom architecture we created new classes in order to add a BiLSTM and CRF layer. While BiLSTM is commonly included in the standard PyTorch library, the implementation of the CRF we used comes from the `pytorch-crf`[5] library. The model classes from HuggingFace were modified by introducing a BiLSTM layer between the transformer and the linear classifier. The CRF layer then employs the Viterbi Algorithm to calculate the loss and to determine the most probable label. In order to train these models, we used the `Trainer` class of transformers with the parameters describe in Table 6.

Parameter	**Value**
batch size	8 / 4
BM - epochs	3
CM - epochs	5
optimizer	AdamW
learning_rate	5×10^{-5}
scheduler	linear
weight_decay	0.01
warmup_ratio	0.1
precision	16-bit

Table 6: Key training procedure parameters

A dropout layer with rate 0.5 between the first and second BiLSTM layer was used. A special treatment was reserved for RoBERTa based models, since it is trained on cleaned data, in the end we developed a labels remapping function that uses

[5]https://pytorch-crf.readthedocs.io/en/stable/

Regex patterns to remap predictions on clean data in the original raw text. This process allowed us to increase performance of the baseline with RoBERTa from 80.08% to 86.7% (shown in the notebook).

In accordance with the challenge guidelines, the primary evaluation metric used in this study was the **strict** version of the **F1-score**. For a prediction to be deemed correctly classified, it must not only predict the correct class but also have a perfect match between the predicted entity words and the actual entity words. Apart from that, we also monitored the Precision, Recall and the partial match F1-score, in which just a partial overlap is required. The results obtained on the validation and test set (originally provided as dev-set) are shown in Table 7 and Table 8. All the experiments have been conducted on Google Colab with free plan.

Model	**Validation**			**Test**		
	P	**R**	**F1**	**P**	**R**	**F1**
BM1	81.2	86.5	84.1	84.4	89.0	86.7
BM2	78.0	82.2	80.2	82.0	88.7	85.2
BM3	81.3	86.8	84.0	84.2	90.1	87.1
CM1	76.0	82.3	79.0	85.5	88.4	87.0
CM2	**85.3**	**86.8**	**84.0**	**85.9**	**90.4**	**88.1**

Table 7: Baseline and custom models performance on validation and test set

Named Entity	**P**	**R**	**F1 strict**	**F1 partial**
ORG	**60.2**	**68.6**	**64.1**	**75.0**
WITNESS	93.4	98.3	95.8	97.5
COURT	91.2	91.2	91.2	95.3
CASE_NUMBER	72.8	88.4	79.9	83.6
RESPONDENT	78.0	80.0	79.0	89.2
OTHER_PERSON	88.9	90.2	89.6	96.8
PETITIONER	91.9	96.7	94.2	95.8
PRECEDENT	68.0	76.8	72.1	83.3
STATUTE	90.2	95.0	92.5	95.0
JUDGE	93.1	93.7	93.4	96.0
DATE	**96.0**	**97.3**	**96.7**	**98.0**
GPE	73.8	89.1	80.7	85.6
LAWYER	95.3	95.4	95.3	97.5
PROVISION	90.2	96.5	93.3	94.9
ALL	**85.9**	**90.4**	**88.1**	**92.7**

Table 8: Best model entity-wise performance on test set

B.6 Discussion

From the results in Table 7 it's clear that the best base for our architecture was XLNet, since it out-

Model	**F1**
BM1	84.75
BM2	82.32
BM3	86.04
CM1	85.80
CM2	**87.43**

Table 9: Models performance on submission set

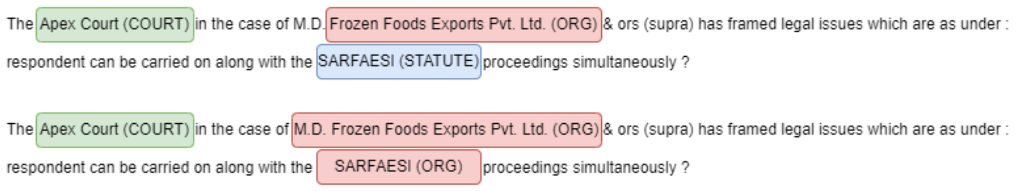
performed InLegalBERT and RoBERTa in both baseline and custom models. The results of our best models (Table 9) for the challenge's submission are slightly worse but in line with the performance on our test set. Comparing them with the one obtained by the challenge's organizers [7] we can claim a +5% on their Transformer+Linear model (86% vs 81%), but a -3.6% on their RoBERTa + Transition based dependency parser (87.43% vs 91.1%).

The comparison between the first type of architecture holds, as they are largely equivalent. The improvements observed in our study may be attributed to differences in training settings. However, such a conclusion cannot be drawn for the second type of architecture, as the details regarding the implementation of the Transition-based dependency parser are limited.

The use of BiLSTM and CRF on top led to slight improvements, similarly to the results of the ablation study of [17]. The entity-wise performance were also very predictable, the best F1-scores are for classes marked by discriminating words in their immediate context, like **dates** that present a typical structure, or **lawyers** that are usually introduced by *"Av."*. The worst performance has been for the organization entity (**ORG**).

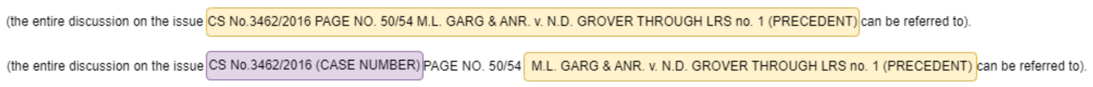
In our notebook we have deeply analyzed some errors for this entity class and we found some typical trends in them:

- Organizations are usually reported with acronyms in upper case. Since our model is case sensitive, this information is crucial and in some cases could lead to mislabeling (Figure 5a).
- Long names for organizations are problematic. The presence of punctuation leads the model to split the entity labeling.
- When ORGs are followed by reference to a law/article/case they can be confused with PRECEDENT that often presents similar structure.
- A sequence of capitalized words can also be confused with the name of an organization.


The Apex Court (COURT) in the case of M.D. Frozen Foods Exports Pvt. Ltd. (ORG) & ors (supra) has framed legal issues which are as under :
respondent can be carried on along with the SARFAESI (STATUTE) proceedings simultaneously ?

The Apex Court (COURT) in the case of M.D. Frozen Foods Exports Pvt. Ltd. (ORG) & ors (supra) has framed legal issues which are as under :
respondent can be carried on along with the SARFAESI (ORG) proceedings simultaneously ?

(a) **ORG**: capitalization confuses the model.


(the entire discussion on the issue CS No.3462/2016 PAGE NO. 50/54 M.L. GARG & ANR. v. N.D. GROVER THROUGH LRS no. 1 (PRECEDENT) can be referred to).

(the entire discussion on the issue CS No.3462/2016 (CASE NUMBER) PAGE NO. 50/54 M.L. GARG & ANR. v. N.D. GROVER THROUGH LRS no. 1 (PRECEDENT) can be referred to).

(b) **PRECEDENT**: the case number is not aggregated with the precedent it's referring to.

Figure 5: Examples of typic errors, others are reported in the notebook

Since a prediction to be considered as correct must have the exact boundaries and class, longer entities are intrinsically more complex and so they have lower scores: a clear example is PRECEDENT which has on average 11 words in our test set. Beside that, as discussed by the challenge's organizers in [7], a lot of errors are due to the fact that our model doesn't have a global view of the document, but only of a standalone judgement sentence or preamble.

Therefore, the model does not consider information typically included in the preamble of court judgments when predicting entities in a sentence. This leads to frequent errors, such as mistaking a PRECEDENT for a CASE NUMBER (as shown in Figure 5b) or person's roles in court judgments. To reduce verbosity, court judgments only fully quote the precedent the first time, subsequently citing it with just the case number or the first person/institution involved. To address these issues in future work, we could implement a post-processing step [7] or find a way to incorporate document-level context into our model.

7 Conclusion

Given the significance of automating intermediate tasks within the judicial process in the face of growing numbers of pending legal cases in populous countries, the LegalEval challenge calls for the development of NLP techniques tailored to the legal domain.

For **Task A**, we proposed a transformer-based approach for classifying rhetorical roles in legal documents. Our experiment showed that fine-tuning transformer-based models pre-trained on legal text in a context-aware manner led to improved performance in this task. Our approach leverages the ability of the models to accurately segment even long legal documents by incorporating context information to enhance sentence representations. This was found to be more effective compared to the simple single sentence classification transformers pre-trained on either general or legal texts. Thanks to this approach, the classification model utilizing InLegalBert as a transformer achieved 81.12% Micro-F1 on the hidden test set. However, the model shows limited discriminating capacity with respect of some minority classes. The imbalance in the class distribution is likely due to the nature of legal documents, which contain long discussions and statements by the court and parties in the core sections of the document. A potential solution to this challenge is to use a multilabel setup, which would enable the model to predict multiple classes per sample. This would allow for further investigation of the predicted classes.

For **Task B**, we proposed a transformer-based approach with a dependency parser to detect and classify entities in legal documents. Our experiments showed that fine-tuning a transformer-based model with a simple classification head is already a good solution for this NER task, but adding a dependency parser on top can be useful to increase the performances. Indeed our custom model reached an higher score, but as expected, considering the long training and computational power availability for the work of [7], our approach was not able to get too close to the results of the best proposed baseline. Beside that, a main limitation of our model was that it doesn't process an entire document but only a single sentence. In their paper the organizers proposed some post-processing steps to consider document level context, nonetheless

we didn't work on that since the true goal of this competition was to develop an end-to-end neural architecture. As future improvement for our model we could experiment some techniques to inject document level information when processing a single sentence.
To conclude, an ideal evaluation pipeline for legal documents could entail a sequential execution of sentence classification and Named Entity Recognition, utilizing the predicted Rhetorical Role to enhance the performance of the latter.

8 Links to external resources

- LegalEval challenge website
- LegalEval challenge leaderboard
- Task A: RR Segmentation Training set
- Task A: RR Segmentation Development set
- Task B: Legal NER Training set
- Task B: Legal NER Development set
- GitHub repository: code

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