An Empirical Study on Cross-Lingual and Cross-Domain Transfer for Legal Judgment Prediction

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Abstract

Cross-lingual transfer learning has proven useful in a variety of NLP tasks, but it is understudied in the context of legal NLP, and not at all on Legal Judgment Prediction (LJP). We explore transfer learning techniques on LJP using the trilingual Swiss-Judgment-Prediction (SJP) dataset, including cases written in three languages (German, French, Italian). We find that Cross-Lingual Transfer (CLT) improves the overall results across languages, especially when we use adapter-based fine-tuning. Finally, we further improve the model's performance by augmenting the training dataset with machine-translated versions of the original documents, using a $3\times$ larger training corpus. Further on, we perform an analysis exploring the effect of cross-domain and cross-regional transfer, i.e., train a model across domains (legal areas), or regions. We find that in both settings (legal areas, origin regions), models trained across all groups perform overall better, while they also have improved results in the worst-case scenarios. Finally, we report improved results when we ambitiously apply cross-jurisdiction transfer, where we augment our dataset with Indian legal cases originally written in English.

1 Introduction

Rapid development in CLT has been achieved by pre-training transformer-based models in large multilingual corpora (Conneau et al., 2020; Xue et al., 2021), where these models have state-of-the-art results in multilingual NLU benchmarks (Ruder et al., 2021). Moreover, adapter-based fine-tuning (Houlsby et al., 2019; Pfeiffer et al., 2020) has been proposed to minimize the misalignment of multilingual knowledge (alignment) when CLT is applied, especially in a zero-shot fashion, where the target language is unseen during training. CLT is severely understudied in legal NLP applications with the exception of Chalkidis et al. (2021a) who experimented with several methods for CLT on MultiEURLEX, a newly introduced multilingual legal topic classification dataset, including EU laws.

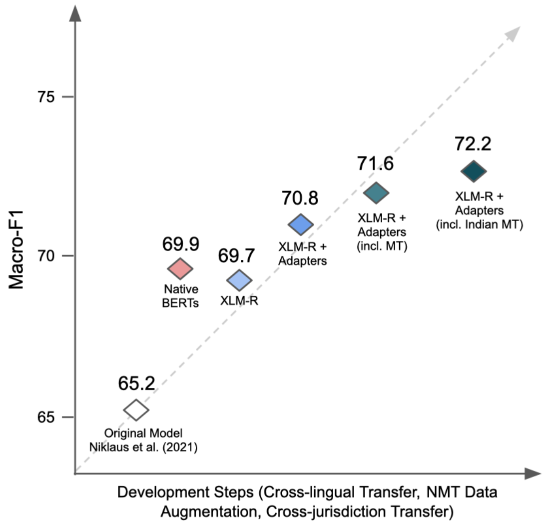

Figure 1: Performance improvement through several development steps (e.g., cross-lingual transfer, data augmentation via machine translations, cross-jurisdiction transfer) considered in our work.

To the best of our knowledge, CLT has not been applied to the LJP task (Aletras et al., 2016; Xiao et al., 2018; Malik et al., 2021), where the goal is to predict the verdict (court decision) given the facts of a legal case. Following the work of Niklaus et al. (2021), we experiment with their newly released trilingual Swiss-Judgment-Prediction (SJP) dataset, containing cases from the Federal Supreme Court of Switzerland (FSCS), written in three official Swiss languages (German, French, Italian).

The dataset covers four core legal areas (public, penal, civil, and social law) and courts originated in eight regions of Switzerland (Zurich, Ticino, etc.), which poses interesting new challenges on model robustness / fairness and the effect of cross-domain and cross-regional knowledge sharing. In their experiments, Niklaus et al. (2021) find that the performance in cases written in Italian is much lower compared to the rest, while also performance varies a lot across regions and legal areas.

In this work, we pose and examine three main research questions: (a) Is cross-lingual transfer beneficial across all or some of the languages?, (b) Do models benefit from cross-domain and cross-regional transfer?, and (c) Can we leverage data from another jurisdiction to improve performance? The contributions of this paper are fourfold:

- We explore, for the first time, the application of cross-lingual transfer learning in the challenging task of Legal Judgment Prediction (LJP) in several settings. We find that a pre-trained language model trained in a multilingual fashion, outperforms its monolingual counterparts, especially when we use Adapter layers and augment the training data with machine-translated versions of the original documents (3× larger training corpus) with larger gains in a low-resource setting (Italian). For the first time, we apply multilingual fine-tuning on the legal judgment prediction task, leading to promising results.
- We perform cross-domain and cross-regional analyses exploring the effects of cross-domain (and cross-regional) transfer, i.e., train a model across domains, with respect to the relevant legal areas (e.g., civil, penal law) or regions (e.g., Zurich, Ticino). We find that in both settings (legal areas, regions), models trained across all groups perform overall better and more robustly; while always improving performance in the worst-case (region or legal area) scenario.
- We also report improved results when we apply cross-jurisdiction transfer, where we further augment our dataset with Indian legal cases originally written in English.
- We release the augmented dataset (incl. 100k machine-translated documents) and our code for replicability and future experimentation.[1]

The cumulative performance improvement amounts to 7% overall and 16+% in the low-resource Italian subset, compared to the best reported scores in Niklaus et al. (2021).

2 Related Work

Legal Judgment Prediction (LJP) is the task, where given the facts of a legal case, a system has to predict the correct outcome (legal judgement). Many prior works experimented with some forms of LJP, however, the precise formulation of the LJP task is non-standard as the jurisdictions and legal frameworks vary. Aletras et al. (2016); Medvedeva et al. (2018); Chalkidis et al. (2019) predict the plausible violation of European Convention of Human Rights (ECHR) articles of the European Court of Human Rights (ECtHR). Xiao et al. (2018, 2021) study Chinese criminal cases where the goal is to predict the ruled duration of prison sentences and/or the relevant law articles.

Another setup is followed by Şulea et al. (2017); Malik et al. (2021); Niklaus et al. (2021), which use cases from Supreme Courts (French, Indian, Swiss, respectively), hearing appeals from lower courts relevant to several fields of law (legal areas). Across tasks (datasets), the goal is to predict the binary verdict of the court (approval or dismissal of the examined appeal) given a textual description of the case. None of these works have explored neither cross-lingual (i.e., models trained in multiple languages), nor cross-jurisdiction transfer, (i.e., from one jurisdiction to another), while the effects of cross-domain and cross-regional transfer are also not studied (analyzed).

Cross-Lingual Transfer (CLT) is a flourishing topic with the application of pre-trained transformer-based models trained in a multilingual setting (Devlin et al., 2019; Lample and Conneau, 2019; Conneau et al., 2020; Xue et al., 2021) excelling in NLU benchmarks (Ruder et al., 2021). Adapter-based fine-tuning (Houlsby et al., 2019; Pfeiffer et al., 2021a) has been proposed as an anti-measure to mitigate misalignment of multilingual knowledge when CLT is applied, especially in a zero-shot fashion, where the target language is unseen during training (or even pre-training).

Meanwhile, CLT is understudied in legal NLP applications. Chalkidis et al. (2021a) experiment with standard fine-tuning, while they also examined the use of adapters (Houlsby et al., 2019) for zero-shot CLT on a legal topic classification dataset comprising European Union (EU) laws. They found adapters to achieve the best tradeoff between effectiveness and efficiency. Their work did not examine the use of methods incorporating translated versions of the original documents in any form, i.e., translate train documents or test ones. Other multilingual legal NLP resources (Galassi et al., 2020; Drawzeski et al., 2021) have been recently released, although CLT is not applied in any form.

[1] The links will be released upon acceptance, the code and data examples are provided to reviewers in the submission.

3 Dataset and Task description

3.1 Swiss Legal Judgment Prediction Dataset

We investigate the LJP task on the Swiss-Judgment-Prediction (SJP) dataset (Niklaus et al., 2021). The dataset contains 85K cases from the Federal Supreme Court of Switzerland (FSCS) from the years 2000 to 2020 in German, French, and Italian. The court hears appeals focusing on small parts of the previous (lower court) decision, where they consider possible wrong reasoning by the lower court. The dataset provides labels for a simplified binary (*approval*, *dismissal*) classification task. Given the facts of the case, the goal is to predict if the plaintiff's request is valid or partially valid.

Since the dataset contains rich metadata, such as legal areas and origin regions, we can conduct experiments on the robustness of the models (see Sections 4.4.2 and 4.4.1). The dataset is not equally distributed; in fact, there is a notable representation disparity where Italian have far fewer documents (4.2k), compared to German (50k) and French (31k). Representation disparity is also vibrant with respect to legal areas and regions.

3.2 Indian Legal Judgment Prediction Dataset

The Indian Legal Document Corpus (ILDC) dataset (Malik et al., 2021) comprises 30K cases from the Indian Supreme Court in English. The court hears appeals that usually include multiple petitions and rules a decision ("accepted" v/s "rejected") per petition. Similarly to Niklaus et al. (2021), Malik et al. released a simplified version of the dataset, dubbed *ILDCmulti* in the original article, with binarized labels. In effect, the two datasets (SJP, ILDC) target the very same task (partial or full approval of plaintiff's claims), nonetheless in two different jurisdictions (Swiss Federation and India).

Our main goal, when we use ILDC as a complement of SJP, is to assess the possibility of cross-jurisdiction transfer from Indian to Swiss cases (see section 4.5), an experimental scenario that has not been explored so far in the literature.

3.3 NMT-based Data Augmentation

In our experiments, we perform data augmentation using machine-translated versions of the original documents, i.e., translate a document originally written in a single language to the other two (e.g., from German to French and Italian). We performed the translations using the EasyNMT[2] framework utilizing the *many-to-many* M2M_100_418M model of (Fan et al., 2020), since the *one-to-one* OPUS-MT (Tiedemann and Thottingal, 2020) models did not have any model available from French to Italian at the time of the experiments. A manual check of some translated samples showed sufficient translation quality. We release the machine-translated additional dataset to the public for future consideration on cross-lingual experiments.

To the best of our knowledge, machine translation for data augmentation has not been studied in legal judgment prediction so far. As we show in the experiments (see Section 4.3), the translations are effective, leading to an average improvement of 1.6% macro-F1 for fine-tuning and 0.8% for adapters (see Table 1). For the low-resource Italian subset, the improvement even amounts to 3.2% macro-F1 for fine-tuning and 1.6% for adapters.

4 Experiments

4.1 Hierarchical BERT

Since the Swiss-Judgment-Prediction dataset contains many documents with more than 512 tokens (90% of the documents are up to 2048), we use Hierarchical BERT models similar to (Chalkidis et al., 2019; Niklaus et al., 2021) to encode up to 2048 tokens per document (4×512 blocks).

We split the text into consecutive blocks of 512 tokens and feed the first 4 blocks to a shared standard BERT encoder. Then, we aggregate the block-wise `CLS` tokens by passing them through another 2-layer transformer encoder, followed by max-pooling and a final classification layer.

We re-use and expand the implementation released by Niklaus et al. (2021),[3] which is based on the Hugging Face library (Wolf et al., 2020). Notably, we first improve the masking of the blocks. Specifically, when the document has less than the maximum number (4) of blocks, we pad with extra sequences of `PAD` tokens, without the use of special tokens (`CLS`, `SEP`), as was previously performed. This minor technical improvement seems to affect the model's performance at large (Table 1).

We experiment with monolingually pre-trained BERT models and XLM-R (approx. 550M parameters) of Conneau et al. (2020), available at `https://huggingface.co/models`. Specifically, for monolingual experiments (Native BERTs), we use German-BERT (approx. 110M parameters)

[2] `https://github.com/UKPLab/EasyNMT`

[3] `https://github.com/JoelNiklaus/SwissJudgementPrediction`

Model	#M	German (de)	French (fr)	Italian (it)	All languages
A1. *Monolingual: Fine-tune on the* **tgt training set (src = tgt)** — Baselines					
Linear (BoW)	N	52.6 ± 0.1	56.6 ± 0.2	53.9 ± 0.6	54.4 ± 0.3
Prior SotA (Niklaus et al., 2021)	N	68.5 ± 1.6	70.2 ± 1.1	57.1 ± 0.4	65.2 ± 0.8
NativeBERT	N	69.6 ± 0.4	72.0 ± 0.5	68.2 ± 1.3	69.9 ± 1.6
XLM-R	N	68.2 ± 0.3	69.9 ± 1.6	59.7 ± 10.8	65.9 ± 4.5
A2. *Monolingual: Fine-tune on the* **tgt training set incl. machine-translations (src = tgt)**					
NativeBERT	N	70.0 ± 0.7	71.0 ± 1.3	71.9 ± 2.5	71.0 ± 0.8
XLM-R	N	68.8 ± 1.4	70.7 ± 2.1	71.9 ± 2.6	70.4 ± 1.3
B1. *Cross-lingual: Fine-tune on* **all training sets (src ⊂ tgt)**					
XLM-R	1	68.9 ± 0.3	71.1 ± 0.3	68.9 ± 1.4	69.7 ± 1.0
XLM-R + Adapters	1	69.9 ± 0.6	71.8 ± 0.7	70.7 ± 1.8	70.8 ± 0.8
B2. *Cross-lingual: Fine-tune on* **all training sets incl. machine-translations (src ⊂ tgt)**					
XLM-R	1	70.2 ± 0.5	71.5 ± 1.1	72.1 ± 1.2	71.3 ± 0.7
XLM-R + Adapters	1	**70.3** ± 0.9	**72.1** ± 0.8	**72.3** ± 2.1	**71.6** ± 0.8
C. *Zero-shot Cross-lingual: Fine-tune on* **all training sets excl. tgt language (src ≠ tgt)**					
XLM-R	1	58.4 ± 1.2	58.7 ± 0.8	68.1 ± 0.2	61.7 ± 4.5
XLM-R + Adapters	1	62.5 ± 0.6	58.8 ± 1.5	67.5 ± 2.2	62.8 ± 3.7

Table 1: Test results for all training set-ups (monolingual w/ or w/o translations, multilingual w/ or w/o translations, and zero-shot) w.r.t source (src) and target (tgt) language. Best overall results are in **bold**, and best per setting (group) are underlined. ***The adapter-based multilingually fine-tuned XLM-R model including machine-translated versions** (3× **larger training corpus) has the best overall results***. #M is the number of models trained/used (1, or N=3). The mean and standard deviation are computed across random seeds.

(Chan et al., 2019) for German, CamemBERT (Martin et al., 2020) (approx. 123M parameters) for French, and UmBERTo (approx. 123M parameters) (Parisi et al., 2020) for Italian, similar to Niklaus et al. (2021). These models are considered the best monolingual models in the respective languages.

In our multilingual experiments, we also assess the effectiveness of adapter-based fine-tuning (Houlsby et al., 2019; Pfeiffer et al., 2020), in comparison to standard full fine-tuning. In this setting, adapter layers are placed after all feed-forward layers of a given network (NativeBERT, or XLM-R) and are trained, similarly to the layer-normalization parameters, and in contrast to the rest of the model parameters that remain untouched.

4.2 Experimental Set Up

We follow Niklaus et al. (2021) and report macro-averaged F1 score to account for the high class-imbalance in the dataset (approx. 20/80 approval/dismissal ratio). We repeat each experiment with 3 different random seeds and report the average score and standard deviation across runs (seeds). We perform grid-search and report test results, selecting the hyper-parameters with the best development scores.[4]

4.3 Cross-lingual Transfer

We first examine *cross-lingual transfer*, where the goal is to share (transfer) knowledge across languages, and we compare models in three main settings: (a) *Monolingual*: fine-tuned per language, using either the documents originally written in the language, or an augmented training set including the machine-translated versions of all other documents (originally written in another language),[5] (b) *Cross-lingual*: fine-tuned across languages with or without the additional translated versions, and (c) *Zero-shot cross-lingual*: fine-tuned across a subset of the languages excluding a target language at a time. We present the results in Table 1.

[4]Additional details on model configuration, training, and hyper-parameter tuning can be found in Appendix A.

[5]We use the EasyNMT (`https://github.com/UKPLab/EasyNMT`) library to translate all documents using M2M (Fan et al., 2020). Additional details in Section 3.3.

Origin Region	#D	#L	ZH	ES	CS	NWS	EM	RL	TI	FED	All
Zürich (ZH)	8.8k	de	65.5	65.6	63.7	68.2	62.0	57.9	63.2	54.8	62.6
Eastern Switzerland (ES)	5.7k	de	62.9	66.9	62.8	65.2	62.2	60.2	57.8	55.1	61.6
Central Switzerland (CS)	4.8k	de	62.5	65.5	63.2	65.1	60.7	57.8	60.5	55.9	61.4
Northwestern Switzerland (NWS)	5.7k	de	66.0	68.6	65.2	67.9	61.6	57.0	57.1	55.5	62.4
Espace Mittelland (EM)	8.3k	de,fr	64.1	66.6	63.3	66.7	64.0	66.8	63.2	58.4	64.1
Région Lémanique (RL)	13.4k	fr,de	61.0	64.7	60.2	63.7	63.4	69.8	67.6	54.3	63.1
Ticino (TI)	2.3k	it	55.0	56.3	53.2	54.5	56.0	54.7	66.0	53.1	56.1
Federation (FED)	1.3k	de,fr,it	57.5	59.6	56.8	58.9	55.0	56.5	53.5	54.9	56.6
Cross-regional fine-tuning w/o MT data augmentation											
XLM-R	59.7k	de,fr,it	68.5	71.3	67.7	71.2	69.0	71.4	67.4	64.6	68.9
XLM-R + Adapters	59.7k	de,fr,it	**69.2**	**73.9**	67.9	72.6	69.0	**72.1**	70.1	64.2	69.9
Cross-regional fine-tuning with MT data augmentation											
NativeBERT	59.7k	de,fr,it	69.0	72.1	68.6	72.0	69.9	71.9	68.8	64.8	69.6
XLM-R	3×59.7k	de,fr,it	**69.2**	72.9	68.3	**73.3**	69.9	71.7	70.4	**65.0**	70.1
XLM-R + Adapters	3×59.7k	de,fr,it	**69.2**	73.3	**69.9**	73.0	**70.3**	**72.1**	**70.9**	63.8	**70.3**

Table 2: Test results for models (XLM-R with MT unless otherwise specified) trained per region or across all regions. Best overall results are in **bold**, and in-domain are underlined. ***Cross-regional transfer is beneficial or all regions and has the best overall results. The shared multilingual model trained across all languages and regions is comparable with the baseline (monolingual BERT models).*** #D is the number of training examples per origin region. #L are the languages covered.

We observe that the baseline of *monolingually* pre-trained and fine-tuned models (NativeBERT) have the best results compared to the *multilingually* pre-trained but *monolingually* fine-tuned XLM-R (group A1 – Table 1). Augmenting the original training sets with translated versions of the documents (group A2 – Table 1), originally written in another language, improves performance in almost all (5/6) cases (languages per model). Interestingly, the performance improvement in Italian, which has the least documents (less than 1/10 compared to German), is approx. 2%; making Italian the best performing language after augmentation.

We now turn to the *cross-lingual transfer* setting, where we train XLM-R across all languages. We observe that cross-lingual transfer (group B1 – Table 1) improves performance (+4.5% p.p.) across languages compared to the same model (XLM-R), fine-tuned in a monolingual setting (group A1 – Table 1). This finding suggests that cross-lingual transfer (and the inherited benefit of using larger multilingual corpora) has a significant impact, despite the legal complication of sharing legal definitions across languages. Augmenting the original training sets with the documents translated across all languages, further improves performance (group B2 – Table 1); translating the full training set provides a 3× larger training set (approx. 150k in total) that equally represents all three languages.

We also present results in a *zero-shot cross-lingual* setting (group C – Table 1), where XLM-R is trained in two languages and evaluated in the third one (unseen in fine-tuning). We observe that German has the worst performance (approx. 10% drop), which can be justified as German is a *Germanic* language, while both French and Italian are *Romance* and share a larger part of the vocabulary. Contrarily, in case of Italian, the low-resource language in our experiments, strongly benefits from zero-shot cross-lingual transfer, leading to approx. 10% p.p. improvement, compared to the monolingually trained XLM-R.

Across all cross-lingual settings (groups B-C – Table 1), the use of Adapters improves substantially the overall performance. The multilingual adapter-based XLM-R in group B1 (Table 1) has comparable performance to the NativeBERT models of group A2, where the training dataset has been artificially augmented with machine translations. In a similar setting (group B2 – Table 1), the multilingual adapter-based XLM-R in group B2 has the best overall results, combining the benefits of both cross-lingual transfer and data augmentation.

Concluding, cross-lingual transfer with an augmented dataset comprised of the original and machine-translated versions of all documents, has the best overall performance with a vibrant improvement (3% compared to our strong baselines – second part of Group A1 in Table 1) in Italian, the least represented language.

Legal Area	#D	Public Law	Civil Law	Penal Law	Social Law	All Legal Areas
Public Law	15.2k	56.4 ± 2.2	52.2 ± 2.0	59.7 ± 4.9	60.1 ± 5.8	57.1 ± 3.2
Civil Law	11.5k	44.4 ± 7.9	64.2 ± 0.6	45.5 ± 13.1	43.6 ± 5.2	49.4 ± 8.6
Penal Law	11.8k	40.8 ± 10.1	55.8 ± 2.9	**84.5** ± 1.3	61.1 ± 7.5	60.6 ± 15.7
Social Law	9.7k	52.6 ± 4.2	56.6 ± 2.0	69.0 ± 5.5	70.2 ± 2.0	62.1 ± 7.6
Cross-domain fine-tuning w/o MT data augmentation						
XLM-R	59.7k	57.4 ± 2.0	66.1 ± 3.1	81.4 ± 1.4	70.8 ± 2.0	68.9 ± 8.7
XLM-R + Adapters	59.7k	58.4 ± 2.5	66.1 ± 2.4	83.1 ± 1.2	71.1 ± 1.4	69.7 ± 9.0
Cross-domain fine-tuning with MT data augmentation						
NativeBERT	59.7k	58.1 ± 3.0	64.5 ± 3.7	83.0 ± 1.3	71.1 ± 4.3	69.2 ± 9.2
XLM-R	59.7k	58.0 ± 3.0	**67.2** ± 1.6	84.4 ± 0.2	70.2 ± 1.3	**70.0** ± 9.5
XLM-R + Adapters	59.7k	**58.6** ± 2.7	66.8 ± 2.8	83.1 ± 1.3	**71.3** ± 2.4	69.9 ± 8.8

Table 3: Test results for models (XLM-R with MT unless otherwise specified) **fine-tuned** per legal area (domain) or across all legal areas (domains). Best overall results are in **bold**, and in-domain are underlined. ***Cross-domain transfer is beneficial for 3 out of 4 legal areas and has the best overall results.*** The shared multilingual model trained across all languages and legal areas outperforms the baseline (monolingual BERT models). The mean and standard deviations are computed across languages per legal area and across legal areas for the right-most column. #D is the number of training examples per legal area.

4.4 Cross-domain/regional Transfer Analysis

Further on, we want to examine the benefits of transfer learning (knowledge sharing) in other dimensions. Hence, we analyze model performance with respect to legal areas and origin regions.

4.4.1 Origin Regions

In Table 2 we present the results for *cross-regional* transfer. In the top section of the table, we present results with region-specific multilingual (XLM-R) models evaluated across regions (in-region on the diagonal, zero-shot otherwise). We observe that the cross-regional models (two lower groups of Table 2) always outperform the region-specific models. Moreover, cross-lingual transfer is beneficial across cases; while adapter-based fine-tuning further improves results in 5 out of 8 cases (regions). Data augmentation also is beneficial in most cases.

Surprisingly, in the top part of Table 2, in 50% of the cases (regions), the "zero-shot" model (trained in the cases of another region) slightly outperforms the in-region model (e.g., NWS to ZH and vice-versa). We consider two main factors that may explain these results: (a) number of cases per region, and (b) the topical similarity of the training and test subsets across different regions.[6] None of these factors can effectively explain with the test results. There are also other confounding factors (e.g., language), i.e., models trained on the cases of either Espace Mittelland (EM) or Région Lémanique (RL), both bilingual with 8-10k cases, have the best results across all single-region models, hence a further exploration of these dynamics is needed.

4.4.2 Legal Areas

In Table 3 we present the results for *cross-domain* transfer between legal areas. The results on the diagonal (underlined) are in-domain, i.e., fine-tuned and evaluated in the same legal area. Interesting to note is that the best results (**bold**) are achieved in the cross-domain setting, either by using XLM-R or NativeBERT in 3 out of 4 legal areas. Such an outcome is not predictable based on the current trends in law industry, where legal experts (judges, lawyers, and academics) over-specialize in specific legal areas. Penal law poses the only exception where the domain-specific model outperforms the cross-domain model by a small margin. Again, the results do not correlate with the volume of training data, and suggest that other qualitative characteristics (e.g., the idiosyncrasies of criminal law) are the main reason.

Similarly to the cross-regional experiments, the shared multilingual model (XLM-R) trained across all languages and legal areas with an augmented dataset outperforms the NativeBERT mod-

[6] We consider the distributional similarity (or dissimilarity) w.r.t. legal areas (Table 6 in Appendix B).

els trained in a similar setting, giving another indication that the performance gains from cross-lingual transfer and data augmentation via machine translation are robust domain-wise as well.

4.5 Cross-Jurisdiction Transfer

We, finally, "ambitiously" stretch the limits of transfer learning in LJP and we apply *cross-jurisdiction* transfer, i.e., use of cases from different legal systems, another form of cross-domain transfer. For this purpose, we further augment the SJP dataset of FSCS cases, with cases from the Supreme Court of India (SCI), published by Malik et al. (2021).[7] We consider and translate all (approx. 30k) Indian cases ruled up to the last year (2014) of our training dataset, originally written in English, to all target languages (German, French, and Italian).[8]

In Table 4, we present the results for two cross-jurisdiction settings: *zero-shot* (Only MT Indian), where we train XLM-R on the machine-translated version of Indian cases, and *further augmented* (Original + MT Swiss + MT Indian), where we further augment the (already augmented) training set of Swiss cases with the Indian ones. While zero-shot transfer clearly fails; interestingly, we observe improvement for all languages in the augmented setting. This opens a fascinating new direction for LJP research. The cumulative improvement from all applied enhancements adds up to 7% macro-F1 compared to the XLM-R baseline and 16% to the best method by Niklaus et al. (2021) in the low-resource Italian subset.

Statistical Significance: Since our experiments present several incremental improvements, we want to assess the stability of the performance improvements with statistical significance testing by comparing the most crucial settings. Using Almost Stochastic Order (ASO) (Dror et al., 2019) with a confidence level $\alpha = 0.05$, we find the score distributions of the core models (NativeBERT, w/ and w/o MT Swiss, XLM-R w/ and w/o MT Indian and/or Swiss) stochastically dominant ($\epsilon_{\min} = 0$) over each other in order.

We compared all pairs of models based on three random seeds each using ASO with a confidence level of $\alpha = 0.05$ (before adjusting for all pair-wise comparisons using the Bonferroni correction). Almost stochastic dominance ($\epsilon_{\min} < 0.5$) is indicated in Table 5. We use the deep-significance Python library of Ulmer (2021). Results are presented in Table 5.

[7] Although SCI rules under the Indian jurisdiction (law), while the FSCS under the Swiss one, we hypothesize that both legal systems, primarily civil-based, share core standards, and thus transferring knowledge could potentially have a positive effect. We discuss this matter in Appendix D.

[8] We do not use the original documents written in English, as English is not one of our target languages.

5 Conclusions and Future Work

We examined the application of CLT in Legal Judgment Prediction for the very first time. We found that a multilingually trained model including translated versions (3× larger training corpus) have the best overall results, especially in the low resource setting (Italian). Adapter-based fine-tuning led to even better results. We also examined the effects of cross-domain (legal areas) and cross-regional transfer, which is overall beneficial in both settings, leading to more robust models. Cross-jurisdiction transfer by further augmenting the training set with machine-translated Indian cases improves overall performance. The cumulative improvement from all applied enhancements adds up to 7% macro-F1 compared to the XLM-R baseline and 16% to the best method by Niklaus et al. (2021) in the low-resource Italian subset.

In future work, we would like to explore the use of a legal-oriented multilingual pre-trained model by either continued pre-training of XLM-R, or pre-training from scratch in multilingual legal corpora. Legal NLP literature (Chalkidis et al., 2021b; Zheng et al., 2021) suggests that domain specificity positively affects performance. In another interesting direction, we will consider other data augmentation techniques that rely on textual alternations (Feng et al., 2021; Ma, 2019).

Ethics Statement

The scope of this work is to study LJP to broaden the discussion and help practitioners to build assisting technology for legal professionals and laypersons. We believe that this is an important application field, where research should be conducted (Tsarapatsanis and Aletras, 2021) to improve legal services and democratize law, while also highlight (inform the audience on) the various multi-aspect shortcomings seeking a responsible and ethical (fair) deployment of legal-oriented technologies.

In this direction, we study how we could better exploit all the available resources (from various languages, domains, regions, or even different jurisdictions). This combination leads to models that

Model	Training Dataset	German (de)	French (fr)	Italian (it)	All languages
XLM-R	Original	68.9 ± 0.3	71.1 ± 0.3	68.9 ± 1.4	69.7 ± 1.0
XLM-R + Adapters	Original	69.9 ± 0.6	71.8 ± 0.7	70.7 ± 1.8	70.8 ± 0.8
XLM-R	+ MT Swiss	70.2 ± 0.5	71.5 ± 1.1	72.1 ± 1.2	71.3 ± 0.7
XLM-R + Adapters	+ MT Swiss	70.3 ± 0.8	72.1 ± 0.8	72.1 ± 1.2	72.3 ± 2.1
XLM-R	+ MT Swiss + MT Indian	70.5 ± 0.4	71.8 ± 0.3	**73.5** ± 1.4	72.0 ± 0.9
XLM-R + Adapters	+ MT Swiss + MT Indian	**71.0** ± 0.4	**73.0** ± 0.6	72.6 ± 1.1	**72.2** ± 1.2
XLM-R	MT Indian	50.4 ± 1.5	47.9 ± 1.0	49.5 ± 1.3	49.3 ± 1.0
XLM-R + Adapters	MT Indian	51.6 ± 2.9	49.7 ± 1.4	50.1 ± 1.4	50.5 ± 1.0

Table 4: Test results for cross-jurisdiction transfer. We present results in three settings: *standard* (Original) *augmented* (+ MT Swiss), *further augmented incl. cross-jurisdiction* (+ MT Swiss + MT Indian) and *zero-shot* (MT Indian). Best results are in **bold**. ***Further augmenting with Indian cases is overall beneficial.***

Model Type	M1	M2	M3	M4
M1: NativeBERT	1.0	1.0	1.0	1.0
M2: NativeBERT + MT CH	0.0	1.0	1.0	1.0
M3: XLM-R + MT CH	0.0	0.0	1.0	1.0
M4: XLM-R + MT CH + IN	0.0	0.0	0.0	1.0

Table 5: Almost stochastic dominance ($\epsilon_{\min} < 0.5$) with ASO. + *MT CH* stands for augmentation with machine translation inside the Swiss dataset and + *MT CH+IN* is the code for augmentation with machine-translations with the Swiss **and** Indian dataset.

improve overall performance – more robust models –, while having improved performance in the worst-case scenarios across many important demographic or legal dimensions (low-resource language, worst performing legal area and region).

Nonetheless, irresponsible use (deployment) of such technology is a plausible risk, as in any other application (e.g., content moderation) and domain (e.g., medical). We believe that similar technologies should only be deployed to assist human experts (legal scholars, or legal professionals).

The examined dataset, Swiss-Judgment-Prediction, released by Niklaus et al. (2021), comprises publicly available cases from the FSCS, where cases are pre-anonymized, i.e., names and other sensitive information are redacted. The same applies for the Indian Legal Documents Corpus (ILDC) of Malik et al. (2021).

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A Hyperparameter Tuning

We experimented with learning rates in {1e-5, 2e-5, 3e-5, 4e-5, 5e-5} as suggested by Devlin et al. (2019). However, like reported by Mosbach et al. (2020), we also found RoBERTa-based models to exhibit large training instability with learning rate 3e-5, although this learning rate worked well for BERT-based models. 1e-5 worked well enough for all models. To avoid either over- or under-fitting, we use Early Stopping (Caruana et al., 2001) on development data.

We opted to use the standard Adapters of Houlsby et al. (2019), as the language Adapters introduced by Pfeiffer et al. (2020) are more resource-intensive and require further pre-training per language. We tuned the adapter reduction factor in {2×, 4×, 8×, 16×} and got the best results with 2× and 4×; we chose 4× for the final experiments to favor less additional parameters. We tuned the learning rate in {1e-5, 5e-5, 1e-4, 5e-4, 1e-3} and achieved the best results with 5e-5.

We additionally applied label smoothing (Szegedy et al., 2015) on cross-entropy loss. We achieved the best results with a label smoothing factor of 0.1 after tuning with {0, 0.1, 0.2, 0.3}.

We experiment with monolingually pre-trained BERT models and XLM-R (approx. 550M parameters) of Conneau et al. (2020), available at `https://huggingface.co/models`. Specifically, for monolingual experiments (Native BERTs), we use German-BERT (approx. 110M parameters) (Chan et al., 2019) for German, CamemBERT (Martin et al., 2020) (approx. 123M parameters) for French, and UmBERTo (approx. 123M parameters) (Parisi et al., 2020) for Italian, similar to Niklaus et al. (2021). These models are considered the best monolingual models in the respective languages.

B Distances Between Legal Area Distributions per Origin Regions

In Table 6 we show the Wasserstein distances between the legal area distributions of the training and the test sets per origin region across languages. Unfortunately, this analysis does not explain why the NWS model (zero-shot) outperforms the ZH

	ZH	ES	CS	NWS	EM	RL	TI	FED
ZH	.02	.02	.03	.02	.01	.02	.05	.12
ES	.03	.03	.04	.03	.02	.01	.06	.11
CS	.02	.01	.01	.02	.01	.04	.06	.13
NWS	.05	.04	.06	.04	.04	.03	.04	.09
EM	.03	.03	.04	.02	.03	.03	.04	.10
RL	.06	.05	.07	.05	.05	.05	.04	.07
TI	.07	.07	.08	.05	.07	.08	.02	.06
FED	.10	.10	.12	.09	.10	.10	.06	.02

Table 6: Wasserstein distances between the legal area distributions of the training and the test set per origin region across languages. The training sets are in the columns and the test sets in the rows.

model (in-domain) on the ZH test set, as found in Table 4.4.1.

C Additional Results

In Tables 7, 8, 9 and 10 we present detailed results for all experiments. All tables include both the average score across repetitions, as reported in the original tables in the main article, but also the standard deviations across repetitions.

D Motivation for Cross-Jurisdiction Transfer

Legal systems vary from country to country. Although they develop in different ways, legal systems also have some similarities based on historically accepted justice ideals. Switzerland has a civil law legal system, i.e., statutes (legislation) is the primary source of law, at the crossroads between Germanic and French legal traditions. Contrary, India maintains a hybrid legal system with a mixture of civil, common law and customary, Islamic ethics, or religious law within the legal framework inherited from the colonial era and various legislation first introduced by the British are still in effect in modified forms today.

Although the Supreme Court of India (SCI) rules under the Indian jurisdiction (law), while the Federal Supreme Court of Switzerland (FSCS) under the Swiss one, we hypothesize that the fundamentals of law in two primarily civil law legal systems are quite common, especially in penal law, and thus transferring knowledge could potentially have a positive effect.

E Responsible NLP Research

We include information on limitations, licensing of resources, and computing foot-print, as suggested by the newly introduced Responsible NLP Research checklist.

E.1 Limitations

In this appendix, we discuss core limitations that we identify in our work and should be considered in future work.

Adapter under-performance Contrary to the literature (Pfeiffer et al., 2021a,b; Chalkidis et al., 2021a), in our case, Adapters do not improve in the cross-lingual transfer setting over fine-tuning. Although we tuned both the learning rate and the reduction factor (see Appendix A), we did not manage to improve the performance. So far, we do not have a reasonable explanation for this behavior.

Data size fluctuations We did not control for the sizes of the training datasets, which is why we reported them in the Tables 3, 2 and 4. This mimics a more realistic setting, where the training set size differs based on data availability. However, we cannot completely rule out different performance based on simply more training data.

Mismatch in in/out of region model perfomance As described in Section 4.4.1, certain zero-shot evaluations outperform in-domain evaluations. Although we try to find an explanation for this in Appendix B, it remains an open question.

Re-use of Indian cases Although we have empirical results confirming the statistically significant positive effect of training with additional translated Indian cases, we do not have a thorough legal justification for this finding at the moment.

E.2 Licensing

The SJP dataset (Niklaus et al., 2021) we mainly use in this work is available under a CC-BY-4 license. The second dataset, ILDC (Malik et al., 2021), comprising Indian cases is available upon request. The authors kindly provided their dataset. All used software and libraries (EasyNMT, Hugging Face Transformers, deep-significance, and several other typical scientific Python libraries) are publicly available and free to use, while we always cite the original work and creators. The artifacts (i.e., the translations and the code) we created, target academic research and are available under a CC-BY-4 license.

Legal Area	#D	Public Law	Civil Law	Penal Law	Social Law	All Legal Areas
Public Law	15.2k	56.4 ± 2.2	52.2 ± 2.0	59.7 ± 4.9	60.1 ± 5.8	57.1 ± 3.2
Civil Law	11.5k	44.4 ± 7.9	64.2 ± 0.6	45.5 ± 13.1	43.6 ± 5.2	49.4 ± 8.6
Penal Law	11.8k	40.8 ± 10.1	55.8 ± 2.9	**84.5** ± 1.3	61.1 ± 7.5	60.6 ± 15.7
Social Law	9.7k	52.6 ± 4.2	56.6 ± 2.0	69.0 ± 5.5	70.2 ± 2.0	62.1 ± 7.6
All	59.7k	58.0 ± 3.0	**67.2** ± 1.6	84.4 ± 0.2	70.2 ± 1.3	**70.0** ± 9.5
All (w/o MT)	59.7k	57.4 ± 2.0	66.1 ± 3.1	81.4 ± 1.4	70.8 ± 2.0	68.9 ± 8.7
All (Native)	59.7k	**58.1 ± 3.0**	64.5 ± 3.7	83.0 ± 1.3	**71.1 ± 4.3**	69.2 ± 9.2

Table 7: Test results for models (XLM-R with MT unless otherwise specified) **fine-tuned** per legal area (domain) or across all legal areas (domains). Best overall results are in **bold**, and in-domain are underlined. ***Cross-domain transfer is beneficial for 3 out of 4 legal areas and has the best overall results.*** The shared multilingual model trained across all languages and legal areas outperforms the baseline (monolingual BERT models). The mean and standard deviations are computed across languages per legal area and across legal areas for the right-most column. #D is the number of training examples per legal area.

Legal Area	#D	Public Law	Civil Law	Penal Law	Social Law	All Legal Areas
Public Law	59.7k	57.2 ± 1.8	53.8 ± 2.1	58.9 ± 5.2	61.7 ± 4.1	57.9 ± 2.9
Civil Law	59.7k	41.4 ± 6.6	57.6 ± 1.1	42.8 ± 9.1	43.0 ± 4.1	46.2 ± 6.6
Penal Law	59.7k	37.4 ± 12.8	56.4 ± 2.0	**86.3** ± 0.1	61.6 ± 6.7	60.4 ± 17.4
Social Law	59.7k	51.4 ± 5.8	54.8 ± 2.8	73.9 ± 1.9	70.3 ± 2.2	62.6 ± 9.7
All	59.7k	**58.6** ± 2.7	**66.8** ± 2.8	83.1 ± 1.3	**71.3** ± 2.4	**69.9** ± 8.8
All (w/o MT)	59.7k	58.4 ± 2.5	66.1 ± 2.4	83.1 ± 1.2	71.1 ± 1.4	69.7 ± 9.0

Table 8: Test results for models (XLM-R with MT unless otherwise specified) **adapted** per legal area (domain) or across all legal areas (domains). Best overall results are in **bold**, and in-domain are underlined. The mean and standard deviations are computed across languages per legal area and across legal areas for the right-most column. #D is the number of training examples per legal area.

E.3 Computing Infrastructure

We used an NVIDIA GeForce RTX 3090 GPU with 24 GB memory for our experiments. In total, the experiments took approx. 80 GPU days, excluding the translations. The translations took approx. 7 GPU days per language from Indian to German, French, and Italian. The translation within the Swiss corpus took approx. 4 GPU days in total.

Region	#D	#L	ZH	ES	CS	NWS	EM	RL	TI	FED	All
ZH	8.8k	de	65.5 ± 0.0	65.6 ± 0.0	63.7 ± 0.0	68.2 ± 0.0	62.0 ± 2.9	57.9 ± 6.7	63.2 ± 0.0	54.8 ± 5.1	62.6 ± 4.1
ES	5.7k	de	62.9 ± 0.0	66.9 ± 0.0	62.8 ± 0.0	65.2 ± 0.0	62.2 ± 1.1	60.2 ± 5.3	57.8 ± 0.0	55.1 ± 6.3	61.6 ± 3.6
CS	4.8k	de	62.5 ± 0.0	65.5 ± 0.0	63.2 ± 0.0	65.1 ± 0.0	60.7 ± 1.6	57.8 ± 3.7	60.5 ± 0.0	55.9 ± 0.5	61.4 ± 3.1
NWS	5.7k	de	66.0 ± 0.0	68.6 ± 0.0	65.2 ± 0.0	67.9 ± 0.0	61.6 ± 1.7	57.0 ± 4.9	57.1 ± 0.0	55.5 ± 5.7	62.4 ± 4.9
EM	8.3k	de,fr	64.1 ± 0.0	66.6 ± 0.0	63.3 ± 0.0	66.7 ± 0.0	64.0 ± 0.7	66.8 ± 2.9	63.2 ± 0.0	58.4 ± 0.3	64.1 ± 2.6
RL	13.4k	fr,de	61.0 ± 0.0	64.7 ± 0.0	60.2 ± 0.0	63.7 ± 0.0	63.4 ± 3.3	69.8 ± 2.7	67.6 ± 0.0	54.3 ± 7.2	63.1 ± 4.4
TI	2.3k	it	55.0 ± 0.0	56.3 ± 0.0	53.2 ± 0.0	54.5 ± 0.0	56.0 ± 0.4	54.7 ± 0.9	66.0 ± 0.0	53.1 ± 6.4	56.1 ± 3.9
FED	1.3k	de,fr,it	57.5 ± 0.0	59.6 ± 0.0	56.8 ± 0.0	58.9 ± 0.0	55.0 ± 1.0	56.5 ± 1.1	53.5 ± 0.0	54.9 ± 2.9	56.6 ± 1.9
All	59.7k	de,fr,it	**69.2** ± 0.0	**72.9** ± 0.0	68.3 ± 0.0	**73.3** ± 0.0	**69.9** ± 1.6	71.7 ± 2.8	**70.4** ± 0.0	**65.0** ± 3.9	**70.1** ± 2.5
All (w/o MT)	59.7k	de,fr,it	68.5 ± 0.0	71.3 ± 0.0	67.7 ± 0.0	71.2 ± 0.0	69.0 ± 1.5	71.4 ± 0.3	67.4 ± 0.0	64.6 ± 5.2	68.9 ± 2.2
All (Native)	59.7k	de,fr,it	69.0 ± 0.0	72.1 ± 0.0	**68.6 ± 0.0**	72.0 ± 0.0	**69.9 ± 1.6**	**71.9 ± 0.7**	68.8 ± 0.0	64.8 ± 7.0	69.6 ± 2.3

Table 9: Test results for models (XLM-R with MT unless otherwise specified) **fine-tuned** per region (domain) or across all regions (domains). Best overall results are in **bold**, and in-domain are underlined. The mean and standard deviations are computed across languages per origin region and across origin regions for the right-most column. The regions where only one language is spoken thus show std 0. #D is the number of training examples per origin region. #L are the languages covered.

Region	#D	#L	ZH	ES	CS	NWS	EM	RL	TI	FED	All
ZH	8.8k	de	65.4 ± 0.0	68.7 ± 0.0	63.9 ± 0.0	68.2 ± 0.0	63.6 ± 3.5	61.0 ± 2.8	66.4 ± 0.0	56.3 ± 1.8	64.2 ± 3.8
ES	5.7k	de	64.2 ± 0.0	69.4 ± 0.0	63.9 ± 0.0	66.0 ± 0.0	61.7 ± 2.3	59.4 ± 4.6	61.2 ± 0.0	56.5 ± 6.1	62.8 ± 3.7
CS	4.8k	de	63.1 ± 0.0	66.5 ± 0.0	64.1 ± 0.0	65.0 ± 0.0	61.0 ± 2.6	57.5 ± 2.1	62.2 ± 0.0	56.7 ± 2.5	62.0 ± 3.2
NWS	5.7k	de	65.8 ± 0.0	69.0 ± 0.0	63.8 ± 0.0	67.4 ± 0.0	59.9 ± 3.3	58.6 ± 1.1	58.9 ± 0.0	54.2 ± 2.7	62.2 ± 4.8
EM	8.3k	de,fr	63.9 ± 0.0	67.5 ± 0.0	64.4 ± 0.0	66.8 ± 0.0	64.7 ± 0.5	69.1 ± 1.7	66.4 ± 0.0	59.5 ± 1.0	65.3 ± 2.7
RL	13.4k	fr,de	62.3 ± 0.0	66.2 ± 0.0	62.0 ± 0.0	64.7 ± 0.0	65.2 ± 4.2	70.8 ± 6.8	65.5 ± 0.0	56.9 ± 6.0	64.2 ± 3.7
TI	2.3k	it	56.4 ± 0.0	62.1 ± 0.0	53.7 ± 0.0	56.3 ± 0.0	55.1 ± 0.2	57.4 ± 1.1	68.3 ± 0.0	50.5 ± 2.3	57.5 ± 5.1
FED	1.3k	de,fr,it	52.7 ± 0.0	52.7 ± 0.0	51.3 ± 0.0	53.1 ± 0.0	52.8 ± 0.7	52.0 ± 2.3	52.8 ± 0.0	50.0 ± 4.0	52.2 ± 1.0
All	59.7k	de,fr,it	**69.2** ± 0.0	73.3 ± 0.0	**69.9** ± 0.0	**73.0** ± 0.0	**70.3** ± 1.9	**72.1** ± 0.7	**70.9** ± 0.0	63.8 ± 6.1	**70.3** ± 2.8
All (w/o MT)	59.7k	de,fr,it	**69.2** ± 0.0	**73.9** ± 0.0	67.9 ± 0.0	72.6 ± 0.0	69.0 ± 2.1	**72.1** ± 0.3	70.1 ± 0.0	**64.2** ± 4.6	69.9 ± 2.9

Table 10: Test results for models (XLM-R with MT unless otherwise specified) **adapted** per region (domain) or across all regions (domains). Best overall results are in **bold**, and in-domain are underlined. The mean and standard deviations are computed across languages per origin region and across origin regions for the right-most column. The regions where only one language is spoken thus show std 0. #D is the number of training examples per origin region. #L are the languages covered.