ABSTRACT
Ambiguity is a characteristic of natural language, which makes expression ideas flexible. However, in a domain that requires accurate statements, it becomes a barrier. Specifically, a single word can have many meanings and multiple words can have the same meaning. When translating a text into a foreign language, the translator needs to determine the exact meaning of each element in the original sentence to produce the correct translation sentence. From that observation, in this paper, we propose ParaLaw Nets, a pretrained model family using sentence-level cross-lingual information to reduce ambiguity and increase the performance in legal text processing. This approach achieved the best result in the Question Answering task of COLIEE-2021.

CCS CONCEPTS
• Computing methodologies → Neural networks; • Applied computing → Law.

KEYWORDS
pretrained model, legal text processing, cross-lingual, sentence-level

1 INTRODUCTION
Transformer [16], the architecture using encoders and decoders with the attention mechanism has become the best practice in many problems. Variations of this model continuously produce new state-of-the-art results in different tasks. The main difference between these variants lies in how the pretraining tasks are designed to take advantage of the latent information in the data. Pretrained models such as BERT [4], GPTs [1, 13, 14], ALBERT [8], ELECTRA [2], and BART [9] are all based on Transformer but have different approaches to the pretraining tasks. Hence, proposals of pretraining tasks are essential contributions to the development of pretrained models.

Transformer-based pretrained models all need effective pretraining tasks to learn latent patterns in the data. The authors of BERT use two tasks, masked language modeling and next sentence prediction to train this model. The idea of the masked language modeling task is that when some words are masked, a good language model should be able to recover the original words. The next sentence prediction is the task that requires BERT to determine whether a sentence is the next one of another sentence.

GPT is a language model that is trained to recognize the next word of a set of given words, the same approach as N-gram language model. Based on GPT, later versions of this model with a huge number of parameters are able to perform different tasks with very few training samples (few-shot learning) or even no training samples at all (zero-shot learning). GPTs authors also introduce the concept of task conditioning which means with the same input, in different tasks the model must output differently. Language models with patterns learned from data can perform many impressive tasks.

In addition to the pretraining tasks of BERT and GPT, there are other proposals that help to improve the effectiveness or efficiency of the model. ALBERT replaces BERT’s next sentence prediction task with sentence order prediction. Instead of simply concluding whether two sentences are consecutive or not, the model needs to predict the order of two consecutive sentences. ELECTRA’s authors proposed replaced token detection as an alternative to the masked language modeling task. With a discriminator and a generator parallelly trained, the language model needs to find out which token is authentic, which is replaced. BART is considered as a combination of BERT and GPT. This model has both prediction and generation capabilities. A series of pretraining tasks which is applied to BART are Token Masking, Token Deletion, Text Infilling, Sentence Permutation, and Document Rotation.

Pretraining tasks are usually formed based on existing data structures. The language modeling tasks are based on the consecutive and co-occurrence structure of words, sentences, and paragraphs. Additionally, there exist many natural data structures that help pretrained models increase their performance. Detecting specific structures contained in data is important to formulate the corresponding tasks.
A translation of a text gives us more information about its meaning than just a set of vocabulary translated into a new language. A sentence in a language may contain many different semantics and depending on the context, the translation needs to be the most appropriate sentence in the target language with the same meaning. For example, as in Figure 1 in Japanese, こんにちは can be a midday greeting or a formal way to say "hello". In consequence, in the morning context, this sentence needs to be translated as "hello" rather than "good afternoon". Likewise, 'I' in English can be translated in a multitude of ways in Japanese. Determining which is the correct translation must depend on the context of the sentence.

It is important to determine the correct context to correctly understand the meaning of a sentence when dealing with difficult documents such as the law. A correct understanding of semantic will not depend on its language of expression. Therefore, using the original version and the translation in parallel can help the model learn the semantic with better precision.

Figure 1: A single word may have multiple translations.

From such observations, we propose ParaLaw Nets, cross-lingual sentence-level pretraining models for legal document processing. The idea is to force the model to learn the context dependence from bilingual sentences. We conduct experiments on COLIEE-2021 data to verify the effectiveness of the method. Our approach is superior to other multilingual approaches such as BERT Multilingual or XLM-RoBERTa.

2 RELATED WORK

2.1 Multilingual and Crosslingual Approaches

The NLP resources are not uniform across languages. The language with the most abundant resources is English. That of other languages is usually much less. Therefore, resources developed in English will later be transferred to other languages. The multilingual nature of resources is often understood as a translation into other languages from English. The aspect of using semantic in multilingual to reduce ambiguity is also worth investigating.

The multilingual implementation was introduced for the first time when the authors of BERT [4] presented this kind of pretrained models. However, the article does not mention in detail how to build this variant of BERT. Fortunately, on their Github 1, the authors state that this model is trained with the 100 largest Wikipedia languages. Common languages are downsampled and less common languages are upsampled to ensure the patterns are learnable across different languages.

Lample et al. [7] proposed the idea of pretraining models using multiple languages. The authors use 3 tasks to train the model: Causal Language Modeling (CLM), Masked Language Modeling (MLM) and Translation Language Modeling (TLM). Among them, TLM is a task that requires many languages, the model uses translation knowledge between languages to fill the missing words in the blanks. According to the authors, this task forces the model to learn the alignment between languages and leverage the context of one language when the context of the other language is not complete.

XLM-RoBERTa [3] is a pretrained model that uses multilingual advantages over 100 languages. This model with a huge amount of training data on these languages achieved state-of-the-art results on different tasks on the GLUE benchmark compared with cross-language baselines. Through the article, the authors also prove the superiority of multilingual models compared with single-language models.

2.2 Pretrained Models in Legal Domain

In the NLP domains, legal document processing needs particular approaches. The legal vocabulary is different from ordinary language, and law sentences often have a complex structure. Pretrained methods in the legal domain have been proved to be competitive with other methods. Most COLIEE-2020 approaches, including the best systems, use pretrained models [12].

The Task 1 winner, cyber team uses a pretrained Transformer model in their implementation for vector representation [5]. To solve Task 2, JNLP team [11] uses the pretrained model based on supporting information to find supporting paragraphs across the legal cases. The Task 3 winner, LLNTU team [6] uses BERT to classify whether an article is relevant to a given legal question or not. For Task 4, JNLP team also pretrains a legal language model from the case law data to generate strong contextual embedding for the model before making predictions in the statute law. With the limited data and narrow specializations, the pretrained models seem to be a competitive approach.

From observing that multilingual information can support to model the meaning of sentences, we propose Paralaw Nets, pretrained models using multilingual pairs of legal sentences. In any linguistic task, especially in the legal domain, it is very important to understand correctly the meaning of a sentence in making predictions. By forcing the model to learn the possibility of the semantic connection between the two sentences, we believe in having a strong pretrained model.

3 PARALAW NETS

3.1 Pretraining

The general idea of this paper’s approach is to utilize the hidden information that is aligned between two sentences in two different languages to train the model. Different from the token-based approach of XLM-RoBERTa, we use sentence-level approach. The semantic understanding ability of a model is judged on how well it predicts the logical order of sentences in different languages. We
propose two approaches called Next Foreign Sentence Prediction (NFSP) and Neighbor Multilingual Sentence Prediction (NMSP).

Not only considering multilingual as an additional version of the pretrained models in English, we believe that the translation information will help the model to have a better understanding of the sentence meaning. When an idea is correctly understood by a model, this model can verify the expression of that idea in all languages. In other words, semantic is expressed through, but not limited by, the language in which it is expressed.

In the NFSP task, the model needs to read two sentences in different languages and determine if their semantic belong to two consecutive sentences in a document. To this end, the model needs to correctly understand the meaning of each sentence. This is intended to reduce ambiguity in the expression of sentences in both languages.

For example, from original sentences as “The weather is nice. Shall we go out?” and their translations “いい天気ね。 Shall we go out?”, we can create 2 positive samples in the training data as:

- The weather is nice. Shall we go out?
- いい天気ね。 Shall we go out?

The negative samples are pairs of a sentence in the original documents and the translation of another random sentence.

NMSP shares a similar approach with NFSP but the training data is generated with more cases. In addition to bilingual pairs, we include pairs of same-language sentences in two languages. If cross-lingual factor is not considered, NFSP has the same approach as BERT’s NSP task. BERT’s NSP critics argue that the Transformer model can rely on co-appearance information to predict the labels of samples in this task. That is, even if the model does not know whether two sentences are consecutive or not, it can still guess the label based on the proximity of the topic. Dealing with that potential issue, our hypothesis is that if the model determines that sentence A follows sentence B, it must also know that sentence B comes before sentence A. In addition, we assign one label to help the model learn that two sentences are not contiguous in a text.

NFSP is a binary classification problem, NMSP is a multi-label classification problem with labels corresponding to the case of random sampling, normal order, reverse order, and non-contiguous.

The data used to pretrain our ParaLaw Nets is bilingual legal documents. Thanks to globalization, legal documents in other languages are often translated into English sentence by sentence. This creates a great edge for ParaLaw Nets in terms of pretraining data. The experimental models introduced in this paper are trained with Japanese-English bilingual legal data. However, this approach can be generalized to all language pairs or groups.

We pretrain models according to the tasks mentioned. The BERT multilingual base model is used as the base model for both NFSP and NMSP. The distilled versions use the configuration and architecture of BERTDistilled [15]. All models are cased configurations. Data for pretraining NFSP contains 239,000 samples, data for pretraining NMSP contains 718,000 samples. The training process is stopped when the performance of the model does not increase on the validation set. Table 1 shows the parameters and the performances in pretraining the models.

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3.2 Finetuning

Next, we finetune the models for the lawfulness classification problem in Task 5 of the COLIEE-2021. Given a statement as a legal question, the model needs to decide whether that statement is true or false. Without the support of lexical-based retrieval systems, the model needs to really understand the meaning of the previously learned propositions, generalize them and apply that knowledge to the question. Table 2 shows examples of this task.

To strengthen the bilingual model, we use original and augmented data in both English and Japanese. Negation is the main method used to create variations of original data. The first negation rule that is matched will be used only once to avoid the negation of the negation. With English negation rules, we reuse the rules proposed by Nguyen et al [10]. Japanese negation rules are derived from basic Japanese syntax. English and Japanese negation rules are shown in Tables 3 and 4.

4 EXPERIMENTS

4.1 Experimental Setup

We do experiments to choose the best models to generate predictions on the blind test set of COLIEE-2021’s organizer. Data in English includes all data provided by the organizer and a portion of the Japanese Civil Code. In the Japanese Civil Code, statements that are represented as lists are removed because their elements are often lengthy and do not express a complete semantic. In addition, it is not a valid approach if we concatenate them without carefully considering the logical semantic of the whole statement. For example, in natural language, and/or conjunction in a sentence may differ from the logical meaning which the sentence expresses. The process of filtering sentences is processed completely automatically based on the XML structure provided by the Japanese Law Translation website 2.

We augment the data by negation rules as described in Section 3. All full sentences in the Japanese Civil Code are considered lawful and their negations are unlawful. With the data provided by the organizers, the sentences already have labels, we create more data by creating negation of the content and reversing the labels. Data after augmentation contains 7,000 sentences, we use 10% for validation data, the rest is for training.

We experiment on the lawfulness classification problem with 6 different models including the original BERT multilingual base model from Google, XLM-RoBERTa, NFSP base, NFSP distilled, NMSP base and NMSP distilled.

4.2 Experimental Results

Training the models, we observed interesting phenomena when training the models using Japanese data. If we use all the data is augmented with the rules in Table 4, all models cannot converge. To solve this problem, we use a simple curriculum learning strategy for Japanese data. We train 3 epochs using augmented data by the first three negation rules before training with the whole dataset. With only the English data, we did not encounter this problem. We believe that this is an indication of the more challenges in understanding Japanese versus understanding English for the cross-lingual models.

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2https://www.japaneselawtranslation.go.jp
Table 1: Parameters and performances in pretraining the models

| Model          | Max Length | Batch Size | Number of Batches | Validation Accuracy |
|----------------|------------|------------|-------------------|---------------------|
| NFSP Base      | 512        | 16         | 24,000            | 94.4%               |
| NFSP Distilled | 512        | 32         | 34,000            | 92.2%               |
| NMSP Base      | 512        | 16         | 320,000           | 88.0%               |
| NMSP Distilled | 512        | 32         | 496,000           | 87.7%               |

Table 2: Examples for COLIEE-2021’s Task 5

| Sentence                                      | Output |
|-----------------------------------------------|--------|
| No abuse of rights is permitted.              | Yes    |
| The age of majority is reached when a person has reached the age of 12. | No     |

Table 3: Rules applied for negation statement generation in English [10]

| Original Statement | Negation Statement Generation |
|--------------------|-----------------------------|
| contains not       | Remove not from original statement  |
| contains shall     | Replace shall with shall not  |
| contains should    | Replace should with should not |
| contains may       | Replace may with may not      |
| contains must      | Replace must with must not    |
| contains is        | Replace is with is not        |
| contains are       | Replace are with are not      |
| contains will be   | Replace will be with will not be |
| contains can       | Replace can with cannot      |
| contains cannot    | Replace cannot with can       |
| contains with      | Replace with with without    |
| contains without   | Replace without with with    |
| contains A         | Replace A with No             |
| contains An        | Replace An with No            |

4.3 Final Runs Result

From the experimental results, we choose three candidates for final runs: NFSP Base, NMSP Base and Original BERT Multilingual.

4.3 Final Runs Result

We run predictions on the English blind test set provided by the COLIEE-2021’s organizer. Among our 3 models, NFSP Base has the best result, next is NMSP Base, and BERT Multilingual has the lowest result. We were also surprised that NFSP Base outperformed trained with our approach. Looking at Table 3 and Table 4, it can be seen that the English negations are related to the word “not”, the negations of Japanese are more diverse and complex. Therefore the model needs more skills to distinguish negation.

Table 5 shows the performance of the models on the validation set. The distilled models and XLM-RoBERTa completely fail to learn in this task. Figures 2-7 plot the loss fluctuation of these models. The loss values fluctuate around 0.7 and do not decrease. The original BERT Multilingual model passes the threshold of 0.7. Although this model has a huge variant loss value after that, its accuracy is better than XLM-RoBERTa and the distilled models. NFSP Base and NMSP Base have loss reduced to below 0.7 and loss variation is much more stable.

From the experimental results, we choose three candidates for final runs: NFSP Base, NMSP Base and Original BERT Multilingual.
Table 4: Rules applied for negation statement generation in Japanese

| Original Statement | Negation Statement Generation |
|--------------------|-------------------------------|
| contains ません     | Replace ません with ます       |
| contains できる    | Replace できる with できない  |
| contains できない  | Replace できない with できる  |
| contains した      | Replace した with しなかった  |
| contains でない    | Replace でない with である    |
| contains できた    | Replace できた with できなかった |
| contains させる    | Replace させる with させない   |
| contains ている    | Replace ている with でいない  |
| contains がない    | Replace がない with ある      |
| contains ではない  | Replace ではない with はある   |
| contains ことがある| Replace ことがある with ことがある |
| contains しなければならない | Replace しなければならない with してはいけません |
| contains ならない  | Replace ならない with なる     |

Table 5: Performance of models on validation set

| Model            | Accuracy |
|------------------|----------|
| NFSP Base        | 71.0%    |
| NFSP Distilled   | 51.1%    |
| NMSP Base        | 79.5%    |
| NMSP Distilled   | 48.9%    |
| XLM-RoBERTa      | 51.1%    |
| BERT Multilingual| 64.1%    |

Figure 5: Loss fluctuation of NMSP Distilled.
Figure 6: Loss fluctuation of NFSP Base.
Figure 7: Loss fluctuation of NFSP Distilled.

NMSP Base and stayed first on the leaderboard. This may indicate that the test set distribution is somewhat biased against the latent features that the NFSP learned, which is not present in our validation set. However, the test set results support the notion that pretraining with cross-lingual information by our approach helps the model learn more accurately on finetuned tasks.

5 CONCLUSIONS

This paper proposes an approach using sentence-level cross-lingual information to pretrain transformer models before finetuning on the specific task. Taking advantage of cross-lingual resources in legal documents, we introduce NFSP and NMSP models which have impressive performance in our experiments as well as in COLIEE-2021’s blind test. The idea of this study is applicable to problems with aligned translation data as legal text processing.

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REFERENCES

[1] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. arXiv preprint arXiv:2005.14165 (2020).
Table 6: Result of final runs on the test set, the underlined lines refer to our models

| Team | Run ID       | Correct     | Accuracy  |
|------|--------------|-------------|-----------|
|      | BaseLine     | No 43/All 81| 0.5309    |
| JNLP | JNLP.NFSP    | 49          | **0.6049**|
| UA   | UA_parser    | 46          | 0.5679    |
| JNLP | JNLP.NMSP    | 45          | 0.5556    |
| UA   | UA_elmo      | 40          | 0.4938    |
| TR   | TRDistillRoberta | 44      | 0.5432    |
| KIS  | KIS_2        | 41          | 0.5062    |
| KIS  | KIS_3        | 41          | 0.5062    |
| UA   | UA_BERT      | 40          | 0.4938    |
| JNLP | JNLP.BERT_Multilingual | 38      | 0.4691    |
| KIS  | KIS_1        | 35          | 0.4321    |
| TR   | TRGPT3Ada    | 35          | 0.4321    |
| TR   | TRGPT3Davinci| 35          | 0.4321    |

[2] Kevin Clark, Minh-Thang Luong, Quoc V Le, and Christopher D Manning. 2020. Electra: Pre-training text encoders as discriminators rather than generators. arXiv preprint arXiv:2003.10555 (2020).

[3] Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Unsupervised cross-lingual representation learning at scale. arXiv preprint arXiv:1911.02116 (2019).

[4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. arXiv preprint arXiv:1810.04805 (2018).

[5] Westermann Hannes, Savelka Jaromir, and Benyekhlef Karim. 2020. Paragraph Similarity Scoring and Fine-Tuned BERT for Legal Information Retrieval and Entailment. COLIEE 2020 (2020).

[6] Shao Hsuan-Lei, Chen Yi-Chia, and Huang Sieh-Chuen. 2020. BERT-based Ensemble Model for The Statute Law Retrieval and Legal Information Entailment. COLIEE 2020 (2020).

[7] Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. arXiv preprint arXiv:1901.07291 (2019).

[8] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. arXiv preprint arXiv:1909.11942 (2019).

[9] Mike Lewis, Yinhan Liu, Naman Goyal, Jianfeng Gao, Aran Vullum, Margaret Mitchell, Mohamed Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461 (2019).

[10] HT Nguyen, V Tran, and LM Nguyen. 2019. A deep learning approach for statute law entailment task in COLIEE-2019. Proceedings of the 6th Competition on Legal Information Extraction/Entailment. COLIEE (2019).

[11] Ha-Thanh Nguyen, Hai-Yen Thi Vuong, Phuong Minh Nguyen, Binh Tran Dang, Quan Minh Bui, Sinh Trong Vu, Chau Minh Nguyen, Vu Tran, Ken Satoh, and Minh Le Nguyen. 2020. JNLP Team: Deep Learning for Legal Processing in COLIEE 2020. arXiv preprint arXiv:2010.08071 (2020).

[12] Juliano Rabelo, Mi-Young Kim, Randy Goebel, Masaharu Yoshioka, Yoshinobu Kano, and Ken Satoh. 2020. Methods for Legal Document Retrieval and Entailment. COLIEE 2020 (2020).

[13] Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training. (2018).

[14] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI blog 1, 8 (2019), 9.

[15] Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2019. DistilBERT, a distilled version of BERT: smaller, faster, cheaper and lighter. arXiv preprint arXiv:1910.01108 (2019).

[16] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. arXiv preprint arXiv:1706.03762 (2017).