SUBLANGUAGE: A SERIOUS ISSUE AFFECTS PRETRAINED MODELS IN LEGAL DOMAIN

Nguyen Ha Thanh  
Japan Advanced Institute of Science and Technology  
nguyenhathanh@jaist.ac.jp

Nguyen Le Minh  
Japan Advanced Institute of Science and Technology  
nguyenml@jaist.ac.jp

September 6, 2021

ABSTRACT

Legal English is a sublanguage that is important for everyone but not for everyone to understand. Pretrained models have become best practices among current deep learning approaches for different problems. It would be a waste or even a danger if these models were applied in practice without knowledge of the sublanguage of the law. In this paper, we raise the issue and propose a trivial solution by introducing BERTLaw, a legal sublanguage pretrained model. The paper’s experiments demonstrate the superior effectiveness of the method compared to the baseline pretrained model.

1 Introduction

Although the ultimate task of NLP is to create models capable of understanding human language, it is a great challenge. Sometimes, even though we communicate in the same language, we cannot understand each other. This misunderstanding occurs when the language background knowledge of parties does not match. In other words, when we do not have enough knowledge about a certain sublanguage, we cannot understand the content represented by it. For example, in English, languages in medicine, science, and cinema have overlap but are not identical. Native speakers can have difficulty reading a specialized article if they don’t have knowledge of that domain. Similarly, a deep learning model that works well on the general domain does not guarantee it will work well in a specialized domain.

The formation of sublanguages in a language is inevitable [15]. Instead of redefining the concepts every time we exchange ideas, building the specialized vocabulary and syntax in the sublanguage helps us to communicate in a more efficient way [6]. In communication, humans can naturally invent and learn new concepts by creating and mapping a concept to the corresponding context, thereby forming a semantic model for it. The language barrier when a lay reader talks to an expert in a particular area is the lack of background knowledge of the sublanguage in that domain. Unlike other domains, although not being experts in the field of law, people are still bound by rights and obligations by the content written in this sublanguage.

Legal English is a branch of English used in legal writing. It has significant differences in terms and linguistic patterns compared to ordinary English. Legal English is used for writing contracts, regulations, and legal documents that are important for everyone. The question to ask is whether the models without legal background knowledge can deliver the results that meet real life’s expectations. Our assumption is that if it is difficult for native speakers to understand Legal English, then the deep learning models also face the same problem. Deep learning models in general and pretrained models in particular are trained based on data. Hence, unless being familiar with Legal English, they will not work well on tasks that use this sublanguage.

Based on the above points, in this paper, we propose and prove the usefulness of using in-domain data to construct the vocabulary and pretrain a model named BERTLaw. Although using the same architecture and training tasks with BERT, this model gave outstanding results in a legal processing competition. This is a testament to the point that, if the model architecture is general enough, to build better systems, we need to pay attention to the data. Before deep learning systems can be involved in part or all of legal work, this is one item of the checklist that needs to be completed.
The main contributions of the paper are as follows. Firstly, we analyze the problems of legal sublanguage existing in current pretraining techniques. Our assumption is that this issue significantly affects the results of processing legal documents. In this paper, we also refer to other studies about Legal Language and its effect on language understanding. Secondly, we introduce BERTLaw as a pretrained model coming along with a specialized vocabulary constructed by data in the legal domain. This model can be a useful resource for law-related downstream tasks. Thirdly, we conduct experiments to prove the effectiveness of the method. Our approach outperformed using BERT pretrained on general data.

2 Related Work

Although Transformer [16] based models are currently the most successful architecture of pretraining methods, this idea predates the advent of these models. The general idea of pretraining methods is that instead of training the model from scratch, we pretrain the model with a large amount of data so it can learn the main relationships of the concepts in the data. Once pretrained, the model can perform better on a smaller amount of finetuning data for specific tasks. In the past decade, a variety of pretraining methods have been introduced and have made constant breakthroughs in NLP.

One of the first pretraining ideas in NLP is using pretrained word embedding. GloVe [13] and Word2Vec [10] are two famous representatives of this approach. Based on the co-occurrence of the words, the authors create a vector space with the relative position determined by the semantic distance between pairs of words. Word2Vec uses the prediction model to learn word relationships while GloVe trains a model based on the co-occurrence matrix. The word vectors represented by these methods not only help to determine the distance between pairs of concepts but also can mathematically interact with each other. With these vectors, we have equations like "Queen = King - Man + Woman".

ELMo [14] approaches the problem from a different perspective from Word2Vec and GloVe. If the two models above always map a fixed vector value to a corresponding word, the authors of ELMo believe that the word vector can only be determined when there is enough context. Therefore, they propose the concept of contextualized word embedding. This observation is plausible since homonyms of different meanings exist widely in natural language. For example, "blue" can be a word for color or a word for mood, we can only determine its exact meaning when there is enough context. Although this is an important step forward in the pretraining methods of NLP, ELMo’s model architecture is bi-directional LSTM [7] which is not so excellent in dealing with long contexts.

Improving the shortcomings in earlier works, pretrained models based on Transformer architectures such as BERT [5], BART [9] or GPT-3 [2] were invented and made a breakthrough in the field of NLP. Transformer architecture with self-attention and encoder-decoder attention can model the constraints in output and input and represent contextualized word embedding in a longer range. Based on CNN, these models can be computed in parallel, thereby speeding up significantly when training on diverse tasks on huge amounts of data. Although sharing the same architecture, these models are generated by different pretraining methods on different data. So far, these models have state-of-the-art performances on benchmark datasets.

The pretraining methods mentioned above all have one thing in common that they use the general domain data. GloVe is pretrained on Wikipedia dump and Gigaword corpora. Word2Vec is pretrained on Google News corpus. ELMo authors used data from Chelba et al. [4], which is a dataset collected and processed from the WMT11 website. BERT and BART are trained on BooksCorpus and English Wikipedia. GPT-3 is trained on Common Crawl, WebText, Book, and Wikipedia datasets. Therefore, investigating and creating a pretrained model with legal data is essential to achieve high performance in this domain.

3 Method

3.1 The Legal Sublanguage Issue

Sublanguage is a problem that exists in all domains. Even so, legal sublanguage is a more serious problem and affects many people. We all live and work on the basis of the law. The misunderstanding of a law by a person or system can affect the interests of many people, even the whole society. As deep learning models increasingly participate in the production and business life of people, this problem is not just a problem for lawyers. In order to build reliable and effective models, this issue needs to be addressed.

The traditional way of writing by lawyers is considered to be unreadable for a lay reader [3]. These terms are rarely used in daily conversation but are often used in drafting legal documents such as contracts, terms of service, or statute law. Legal English critics argue that legal writing should not make a difference in understanding of individuals with different background knowledge [17]. However, the actual legal documents still contain vocabulary and structures that are difficult to understand for most people.
Legal English is commonly used in English-speaking countries that share the same legal tradition. However, this issue is currently not limited to those countries. With widespread economic trade, the language is spoken in a wider range. Countries do not translate their laws into English but to Legal English. Besides, international contracts also mainly use this language. Therefore, the sublanguage of law is becoming a global issue.

This problem is also not limited to human communication but can be a hindrance to deep learning models in NLP. Pretrained models have become best practices among current deep learning approaches for different problems but if we just use them without realizing the existence of this hindrance, it will lead to great risks. Hence, investigating and creating pretrained models in this area has scientific and practical significance.

3.2 **BERT and BERTLaw**

BERT is a Transformers-based model that uses a bi-directional context in the training process. Two unsupervised tasks used to train BERT are Masked Language Modeling and Next Sentence Prediction. BERT also uses subword embedding instead of word embedding or character embedding as in other approaches. We use the same architecture and the pretraining tasks of BERT for BERTLaw but train the model using the legal data. BERTLaw’s configuration is the same as the original BERT Base version.

As mentioned in Section 2, since BERT is trained using the general domain data, we believe that the vocab of this model is not very effective when operating on the legal domain. BERT can use subword embedding to technically avoid unknown word problems. For example, 3 words contravention, intervention, and reconvention are tokenized as follows: contra-vent-ion (3 subwords), intervention (1 subword), and rec-on-vent-ion (4 subwords). Words that do not exist in the vocabulary will be chopped up by BERT into subwords to represent in its embedding space. However, the ability to interpret subword correctly needs to be trained with the appropriate context.

We build the vocab for BERT Law based on our law corpus statistic according to the method of SentencePieces [8]. This approach is language-independent and avoids bias during vocabulary building. In embedding space, subwords can be considered as unit vectors whose combinations make up the entire space. The main subwords representing specific relationships in the domain are sampled and added into the vocabulary.

Comparing BERTLaw and BERT Base vocabulary shows a significant difference in these unit vectors. Figure 1 shows the cardinality of the two vocabulary sets. The figure shows that the intersection of the two vocabularies is less than half of the total vocabulary for each one. This shows an obvious difference between the two models in how the same input sentence is observed.

![Figure 1: The cardinality of two vocabulary sets of BERT Base and BERT Law.](image)

The data we use is the set of American legal cases with 8.2 million sentences (182 million words). Legal cases contain both vocabularies and grammar in common language and legal language, which enable the model to learn the relationship between the concepts of Legal English and ordinary English. We pretrain the model with input length 128 tokens using Google Colab’s TPU. The pretraining process ends when the model converges and there is no change in loss value.
Table 1: BERT Law and BERT Performance on Validation Set and Test Set

| Model      | Validation Accuracy | Test Accuracy  |
|------------|---------------------|----------------|
| BERT Base  | 0.7784              | 0.5625         |
| BERT Law   | 0.8168              | 0.7232         |

Table 2 shows some examples of subwords that exist in BERT Law’s vocabulary but not in BERT. From these examples, it can be seen that the embedding space of BERT is not capable of directly describing the important concepts of the law but indirectly expressed through other subwords. This can affect the performance of the model on downstream tasks. We provide subwords with explanations of them from the two books "American heritate dictionary of the English language" [11] and "A Law Dictionary, Adapted to the Constitution and Laws of the United States" [1]. Most of these terms are difficult to understand for English users, even for native speakers.

4 Experiments

4.1 Experimental Setting

We test the model’s performance through the Task 4 of COLIEE 2020, an annual competition in automatic legal document processing. This task is to answer the bar exam questions to assess the competence of paralegal examinees. Contestants must answer yes/no questions corresponding to each statement given by the exam. The interesting point in our experiment is that the original data for Task 4 of COLIEE 2020 is Japanese data translated into English by the Ministry of Justice of Japan. This illustrates the globalization of Legal English.

We use the same approach proposed by Nguyen et al. [12], consider the task as a lawfulness classification problem. Data for creating the model are sentences in civil code, labeled questions provided by the organizer, and the augmented versions of them. The total data is 5000 samples, of which 90% is used for training, 10% for validation. Test data are provided by the organizer with 112 statements.

The baseline used in our experiment is the original BERT Base by Google. We use the max length value for both models as 128. The models were finetuned on training data in 5 epochs. The result on the test set is returned by the organizer after the model makes its prediction.

4.2 Experimental Result

Table 1 shows the results of the models on validation and test data. Based on this result, we can see a significant difference between the two models. BERT Law outperforms BERT Base by almost 4% on validation data and over 16% on test data. This result supports our hypothesis about the effectiveness of pretraining the model on Legal English.

Although 16% were an impressive result, it was a single-run assessment on the organizers’ test data. The result we care more about is that BERT Law outperforms BERT Base on the validation set consistently. This shows that the difference in how BERT Law and BERT see the data affects their performance on the downstream task. Although the unknown word can be overcome by dividing the word into subwords, BERT’s weight set is not fully trained to model the exact meaning behind those subwords.

Through the experimental results, we can confirm that pretraining models on the sublanguage of the law help them perform better on tasks in this domain. The experimental data are Japanese civil law and the Japanese legal questions translated into English. BERT Law is pretrained using US legal case data. This shows that the terms used in Legal English are consistent across countries. The training of models in this sublanguage is valid not only to English-speaking countries but also to the world.

5 Discussions

Although BERT Law is a concrete instance of this approach, it is possible to create pretrained models based on other architectures and other tasks using this approach. The important message of this paper is that using only the pretrained models as a tool without examining the characteristics of the pretraining data will not fulfill their full potential. In addition, along with benchmark datasets for general domains, we also need benchmark datasets for specialized areas in order to better verify different solutions to sublanguage problems. Without data, all proposals are only theoretical and difficult to apply in practice.
### Table 2: Examples appearing in BERT Law Vocabulary, not in BERT Base Vocabulary.

| Token       | Explanation                                                                                                                                 |
|-------------|--------------------------------------------------------------------------------------------------------------------------------------------|
| ♯♯legal     | Wordpiece in words containing “legal” (e.g. illegal, legally, legality, legalization)                                                       |
| contravention | An act which violates the law, a treaty or an agreement which the party has made.                                                                 |
| construe    | To determine the meaning of the words of a written document, statute or legal decision, based upon rules of legal interpretation as well as normal meanings. |
| demurrer    | An assertion by the defendant that although the facts alleged by the plaintiff in the complaint may be true, they do not entitle the plaintiff to prevail in the lawsuit. |
| depose      | To make a deposition; to give evidence in the shape of a deposition; to make statements that are written down and sworn to; to give testimony that is reduced to writing by a duly qualified officer and sworn to by the deponent. |
| guardianship | The power or protective authority given by law, and imposed on an individual who is free and in the enjoyment of his rights, over one whose weakness on account of his age, renders him unable to protect himself. |
| infringe    | To transgress or exceed the limits of; violate: infringe a contract; infringe a patent.                                                                 |
| malfeasance | The commission of an act that is unequivocally illegal or completely wrongful.                                                                 |
| misdemeanor | Offenses lower than felonies and generally those punishable by fine, penalty, forfeiture, or imprisonment other than in a penitentiary. |
| reimburse   | To repay (money spent); refund.                                                                                                               |
| renounce    | To give up a right; for example, an executor may renounce the right of administering the estate of the testator; a widow the right to administer to her intestate husband’s estate. |
| rescind     | To declare a contract void—of no legal force or binding effect—from its inception and thereby restore the parties to the positions they would have occupied had no contract ever been made. |
| rescission  | The termination of a contract by mutual agreement or as a result of fraud or some legal defect.                                                 |
| revoke      | To invalidate or cause to no longer be in effect, as by voiding or canceling.                                                                 |
| tort        | a civil wrong. Tortious liability arises from the breach of a duty fixed by law; this duty is towards persons generally and its breach is redressable by an action for unliquidated damages. |
| tortious    | Wrongful; conduct of such character as to subject the actor to civil liability under Tort Law.                                               |

In our opinion, among different domains, law is the one that should be given priority in solving the sublanguage problem. As repeated many times in this paper, law is an area that concerns all citizens of every country and everyone. Solving this problem helps us move closer to our goal of having safe, reliable, and equal AI systems. Besides, governments are building policies to regulate AI systems and they need to be accountable. We believe that in the near future, these systems will not be able to explain their decisions to the legal agency without understanding the correct language of the law.

### 6 Conclusions

In this study, we address the legal sublanguage issue for the performance of deep learning systems. Our assumption is that if people have difficulty in understanding Legal English, this is also a barrier to deep learning systems. To verify our assumptions, we created a pretrained model called BERT Law and compared its performance with original BERT Base from Google. The experimental results support our hypothesis. In addition, we discuss the reasons for those results as well as the impacts of this finding. BERT Law and this paper are useful references and resources for legal domain problems to be solved by deep learning.
References

[1] John Bouvier. A Law Dictionary, Adapted to the Constitution and Laws of the United States of America, and of the Several States of the American Union: with References to the Civil and other Systems of Foreign Law, volume 2. GW Childs, 1870.

[2] Tom B Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. arXiv preprint arXiv:2005.14165, 2020.

[3] Donna Bain Butler, Yalun Zhou, and Michael Wei. When the culture of learning plays a role in academic english writing. ESP across Cultures, (10):55–74, 2013.

[4] Ciprian Chelba, Tomas Mikolov, Mike Schuster, Qi Ge, Thorsten Brants, Phillipp Koehn, and Tony Robinson. One billion word benchmark for measuring progress in statistical language modeling. arXiv preprint arXiv:1312.3005, 2013.

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

[6] Alissa J Hartig and Xiaofei Lu. Plain english and legal writing: Comparing expert and novice writers. English for specific purposes, 33:87–96, 2014.

[7] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. Neural computation, 9(8):1735–1780, 1997.

[8] Taku Kudo and John Richardson. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. arXiv preprint arXiv:1808.06226, 2018.

[9] Mike Lewis, Yinhan Liu, Naman Goyal, Vi Hart, Jitendra Chaudhuri, Aravind Heeman, Paulo Ponce, Steven Ruder,自然语言处理与理解. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. arXiv preprint arXiv:1910.13461, 2019.

[10] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781, 2013.

[11] William Morris. American heritage dictionary of the english language. 1969.

[12] Ha-Thanh Nguyen, Vu Tran, and Le-Minh Nguyen. A deep learning approach for statute law entainment task in coliee-2019. 2019.

[13] Jeffrey Pennington, Richard Socher, and Christopher D Manning. Glove: Global vectors for word representation. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP), pages 1532–1543, 2014.

[14] Matthew E Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. Deep contextualized word representations. arXiv preprint arXiv:1802.05365, 2018.

[15] Peter M Tiersma. Legal language. University of Chicago Press, 1999.

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

[17] Richard C Wydick and Amy E Sloan. Plain English for lawyers, volume 4. Carolina Academic Press Durham, NC, 2005.