Processing Long Legal Documents with Pre-Trained Transformers: Modding LegalBERT and Longformer

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Motivation

- **Pre-trained Transformers** are currently the **state-of-the-art** in NLP.
- The quadratic complexity of their attention mechanism restricts the maximum input length of text they can process.
- Legal domain datasets often contain texts far longer than those limits.
- Even **sparse attention** models (e.g., Longformer) especially designed for long texts, still **cannot cope** with **long legal documents**.
- BoW models can process texts of any length, but ignore word order.

LexGLUE Benchmark

Dataset	Source	Text lenç	gth (words)	Instances	Classes	
		Average	Maximum	(training/dev/test)		
ECtHR Task A	Chalkidis et al. (2019)	1.6k	35.4k	9,000 / 1,000 / 1,000	10+1 [¢]	
ECtHR Task B	Chalkidis et al. (2021a)	1.6k	35.4k	9,000 / 1,000 / 1,000	10+1 ^{\$}	
SCOTUS	Spaeth et al. (2020)	6.ok	88.6k	5,000 / 1,400 / 1,400	14	
EUR-LEX	Chalkidis et al. (2021b)	1.1k	140.1k	55,000 / 5,000 / 5,000	100	
LEDGAR	Tuggener et al. (2020)	113	1.2k	60,000 / 10,000 / 10,000	100	
UNFAIR-ToS	Lippi et al. (2019)	33	441	5.532 / 2.275 / 1.1607	8+1 ^{\$}	

* +1 means that some documents aren't relevant to any class.

LexGLUE example

* Example retrieved from ECtHR dataset

1. At the **beginning of the events** relevant to the application, K. had a daughter, P., and a son, M., born in 1986 and 1988 respectively. P.'s father is X and M.'s father is...and **M.'s foster mother died in May 2001**.

[...]

53. On 29 April 1962 **the applicant married Mr A. Gigliozz**i in a religious ceremony which was also valid in the eyes of the law (matrimonio concordatario).", "12. On 23 February 1987...she also withdrew another set of proceedings that she had instituted in the Viterbo Court claiming joint title to property). Large texts containing more than **500** words on average **Multi-Label classification task**

European Court of Human Rights

A2: Right to life

A3: Prohibition of torture

A5: Right to liberty and security

A6: Right to a fair trial

A8: Right to respect for private and family life

A9: Freedom of thought, conscience and religion

A10: Freedom of expression

A11: Freedom of assembly and association

P1-1: Protection of property

Ao: No violation

Prior work

Sparse attention variants

- These models combine a local windowed attention with a global attention and achieve **linear complexity**.
- Longformer (Beltagy et al. 2020), BigBird (Zaheer et al., 2020), ETC (Ainslie et al., 2020).

Hierarchical Transformers

- Use models like BERT to separately encode each paragraph of the input.
- Then additional layers to make the paragraph embeddings aware of surrounding paragraphs.
- Hierarchical LegalBERT (Chalkidis et al. 2020), SMITH (Yang et al., 2020).

Our contribution (1): BOW BERT variants



(a) TFIDF-SRT-EMB-Legal-BERT

 $S = (W^{1}_{[10]}, W^{2}_{[32]}, W^{3}_{[10]}, W^{4}_{[21]}, W^{5}_{[10]}, W^{6}_{[64]}, W^{7}_{[21]}, W^{8}_{[32]}, W^{9}_{[87]}, W^{10}_{[64]})$

Our contribution (2): Longformer extensions

(b) Longformer-8192-PAR

Can process up to **8,192** tokens whereas the original version can handle only up to **4,096**



 $S = (W^{1}_{100}, W^{2}_{132}, W^{3}_{100}, W^{4}_{121}, W^{5}_{100}, W^{6}_{164}, W^{7}_{121}, W^{8}_{132}, W^{9}_{187}, W^{10}_{164})$

Experimental results (BoW models)

* Results on test data.

Model	ECtHR	ECtHR (Task A)		ECtHR (Task B)		SCOTUS		EUR-LEX		LEDGAR		UNFAIR-ToS	
	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	
TFIDF+SVM	62.6	48.9	73.0	63.8	74.0	64.4	63.4	47.9	87.0	81.4	94.7	75.0	
TFIDF-SRT-LegalBERT	69.8	62.8	78.5	71.9	73.4	61.8	69.6	53.7	86.9	80.8	95.3	80.6	
TFIDF-SRT-EMB-LegalBERT	68.7	63.1	79.0	72.5	73.9	63.6	69.7	53.9	86.5	80.3	95.8	78.7	

Experimental results (BoW models)

[♦] Results on test data.

Model	ECtHR (Task A) *		ECtHR (Task B) *		SCOTUS *		EUR-LEX		LEDGAR		UNFAIR-ToS	
	μ-F1	m-F1	μ-F1	m-F1	µ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1
TFIDF+SVM	62.6	48.9	73.0	63.8	74.0	64.4	63.4	47.9	87.0	81.4	94.7	75.0
TFIDF-SRT-LegalBERT	69.8	62.8	78.5	71.9	73.4	61.8	69.6	53.7	86.9	80.8	95.3	80.6
TFIDF-SRT-EMB-LegalBERT	68.7	63.1	79.0	72.5	73.9	63.6	69.7	53.9	86.5	80.3	95.8	78.7
		L	egalBEI	RT variant	ts that re	tain word	l order					
LegalBERT	70.0	64.0	80.4	74.7	76.4	66.5	72.1	57.4	88.2	83.0	96.0	83.0
TFIDF-EMB-LegalBERT	70.0	61.9	79.4	73.5	74.9	64.7	71.6	56.9	88.7	83.4	95.9	82.1

* The results were obtained using the hierarchical version of the corresponding model.

Experimental results (Longformer variants)

[♦] Results on test data.

Method	EC (Tas	ECtHR (Task A) *		ECtHR (Task B) *		SCOTUS *		EUR-LEX		LEDGAR		UNFAIR-ToS	
	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	μ-F1	m-F1	µ-F1	m-F1	μ-F1	m-F1	
Longformer	69.9	64.7	79.4	71.7	72.9	64.0	71.6	57.7	88.2	83.0	95.5	<u>80.9</u>	
Longformer-8192	70.9	62.1	79.2	73.9	73.7	63.6	(Not considered for short document tasks.)						
Longformer-8192-PAR	70.8	62.3	79.0	73.1	73.9	66.0							
LegalLongformer	71.7	63.6	80.5	76.4	76.6	66.9	72.2 56.6 88.8 83.5 <u>95.7</u> 80.6				80.6		
LegalLongformer-8192	71.2	64.3	81.4	74.2	77.5	67.3	(Not considered for short-document tasks.)						
LegalLongformer-8192-PAR	71.4	68.4	79.6	73.9	76.2	66.3							

* The results were obtained using the hierarchical version of the corresponding model.

Performance - Efficiency tradeoff



10/10

Thanks for your attention!



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Prior work

- Hierarchical Transformers
 - Hierarchical LegalBERT (Chalkidis et al. 2020)
 - Smith (Yang et al., 2020)
- Sparse-attention variants
 - Longformer (Beltagy et al. 2020)
 - BigBird
 - ETC



• Longformer (Beltagy et al. 2020)

Model params., memory footprint (GBs/sample), and inference time (sec/sample) * Results on test data.

Method	Params.	ECt	ECtHR*		SCOTUS*		EUR-LEX		LEDGAR		UNFAIR-ToS			
		Mem.	Time	Mem.	Time	Mem.	Time	Mem.	Time	Mem.	Time			
BoW models (word order lost)														
TFIDF-SVM	0.5M	0.1	.001	0.1	.001	0.1	.001	0.1	.001	0.1	.001			
TFIDF-SRT-LegalBert	110M	0.9	.012	0.9	.012	0.9	.012	0.9	.007	0.9	.007			
TFIDF-SRT-EMB-LegalBERT	110M	0.9	.012	0.9	.012	0.9	.012	0.9	.007	0.9	.007			
LegalBERT variants that retain word order														
LegalBERT	110M	1.3	.014	1.3	.014	1.9	.012	1.9	.007	1.9	.007			
TFIDF-EMB-LegalBERT	110M	1.3	.014	1.3	.014	1.9	.012	1.9	.007	1.9	.007			

Model params., memory footprint (GBs/sample), and inference time (sec/sample) * Results on test data.

Method	Params.	ECtHR*		SCOTUS*		EUR-LEX		LEDGAR		UNFAIR-ToS		
		Mem.	Time	Mem.	Time	Mem.	Time	Mem.	Time	Mem.	Time	
Longformer variants (all retain word order)												
TFIDF-SVM	148M	1.7	.164	1.7	.164	1.3 .033 1.3 0.33 1.3 .03					.033	
TFIDF-SRT-LegalBert	151M	2.2	.318	2.2	.318	(Not considered for short-document class)						
TFIDF-SRT-EMB-LegalBERT	151M	2.2	.331	2.2	.331							

LexGLUE Benchmark

Dataset	Source	Subdomain	Task Type	Instances	Classes
ECtHR Task A	Chalkidis et al. (2019)	ECHR	Multi-label classification	9,000 / 1,000 / 1,000	10+1 [¢]
ECtHR Task B	Chalkidis et al. (2021a)	ECHR	Multi-label classification	9,000 / 1,000 / 1,000	10+1 [¢]
SCOTUS	Spaeth et al. (2020)	US Law	Multi-class classification	5,000 / 1,400 / 1,400	14
EUR-LEX	Chalkidis et al. (2021b)	EU Law	Multi-label classification	55,000 / 5,000 / 5,000	100
LEDGAR	Tuggener et al. (2020)	Contracts	Multi-class classification	60,000 / 10,000 / 10,000	100
UNFAIR-ToS	Lippi et al. (2019)	Contracts	Multi-label classification	5,532 / 2,275 / 1,1607	8+1 [¢]

 $^\diamond$ +1 means that some documents aren't relevant to any class.