TopicBERT for Energy Efficient Document Classification

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Abstract

Prior research notes that BERT's computational cost grows quadratically with sequence length thus leading to longer training times, higher GPU memory constraints and carbon emissions. While recent work seeks to address these scalability issues at pre-training, these issues are also prominent in fine-tuning especially for long sequence tasks like document classification. Our work thus focuses on optimizing the computational cost of fine-tuning for document classification. We achieve this by complementary learning of both topic and language models in a unified framework, named TopicBERT. This significantly reduces the number of self-attention operations – a main performance bottleneck. Consequently, our model achieves a 1.4x (~ 40%) speedup with $\sim 40\%$ reduction in CO₂ emission while retaining 99.9% performance over 5 datasets.

1 Introduction

Natural Language Processing (NLP) has recently witnessed a series of breakthroughs by the evolution of large-scale language models (LM) such as ELMo (Peters et al., 2018), BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), XL-Net (Yang et al., 2019) etc. due to improved capabilities for language understanding (Bengio et al., 2003; Mikolov et al., 2013). However this massive increase in model size comes at the expense of very high computational costs: longer training time, high GPU/TPU memory constraints, adversely high carbon footprints, and unaffordable invoices for small-scale enterprises.

Figure 1 shows the computational cost (training time: millisecond/batch; CO₂ emission, and GPU memory usage) of BERT all of which grow quadratically with sequence length (N). We note that this

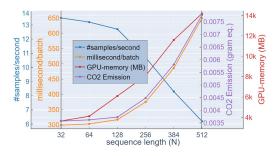


Figure 1: Computational cost vs sequence length

	CO_2
BERT pre-training (NAS) (Strubell et al., 2019)	626k
BERT fine-training (n=512)*	+ 125k

Table 1: Similar to Strubell et al. (2019) who estimate the carbon footprint of BERT during pretraining, we estimate the carbon footprint (lbs of CO₂ equivalent) during finetuning BERT for document classification. *: see *supplementary* material for details.

is primarily due to self-attention operations. Moreover, as we note in Table 1, the staggering energy cost is not limited to only the *pre-training* stage but is also encountered in the fine-tuning stage when processing long sequences as is needed in the task of document classification. Note that the computational cost incurred can be quite significant especially because fine-tuning is more frequent than pre-training and BERT is increasingly used for processing long sequences. Therefore, this work focuses on reducing computational cost in the *fine-tuning* stage of BERT especially for the task of document classification.

Recent studies address the excessive computational cost of large language models (LMs) in the pre-training stage using two main compression techniques: (a) *Pruning* (Michel et al., 2019; Lan et al., 2020) by reducing model complexity, and (b) *Knowledge Distillation* (Hinton et al., 2015; Tang et al., 2019; Turc et al., 2019; Sanh et al., 2019a) which a student model (compact model) is trained

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to reproduce a teacher (large model) leveraging the teacher's knowledge. Finally, in order to process long sequences, Xie et al. (2019) and Joshi et al. (2019) investigate simple approaches of truncating or partitioning them into smaller sequences, e.g., to fit within 512 token limit of BERT for classification; However, such partitioning leads to a loss of discriminative cross-partition information and is still computationally inefficient. In our work, we address this limitation by learning a complementary representation of text using topic models (TM)) (Blei et al., 2003; Miao et al., 2016; Gupta et al., 2019). Because topic models are bag-of-words based models, they are more computationally efficient than large scale language models that are contextual. Our work thus leverages this computational efficiency of TMs for efficient and scalable fine-tuning for BERT in document classification.

Specifically our contributions(1) Complementary Fine-tuning: We present a novel framework: *TopicBERT*, i.e., topic-aware BERT that leverages the advantages of both neural network-based TM and Transformer-based BERT to achieve an improved document-level understanding. We report gains in document classification task with full selfattention mechanism and topical information. (2) Efficient Fine-tuning: TopicBERT offers an efficient fine-tuning of BERT for long sequences by reducing the number of self-attention operations and jointly learning with TM. We achieve a 1.4x (\sim 40%) speedup while retaining 99.9% of classification performance over 5 datasets. Our approaches are model agnostic, therefore we extend BERT and DistilBERT models. Code in available at https: //github.com/YatinChaudhary/TopicBERT.

Carbon footprint (CO_2) estimation: We follow Lacoste et al. (2019) and use ML CO_2 Impact calculator¹ to estimate the carbon footprint (CO_2) of our experiments using the following equation:

 CO_2 = Power consumption × Time (in hours) × Carbon produced by local power grid

where, Power consumption = 0.07KW for NVIDIA Tesla T4 16 GB Processor and Carbon produced by local power grid = 0.61 kg CO₂/kWh. Therefore, the final equation becomes:

$$CO_2 = 0.07kW \times \text{Time (in hours)}$$

 $\times 0.61 \times 1000 \text{ gram eq. CO}_2\text{/kWh}$ (1)

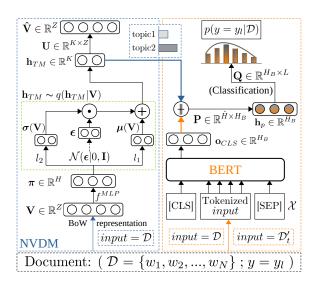


Figure 2: Topic-aware BERT (TopicBERT): Joint fine-tuning of NVDM and BERT; The input in BERT is \mathcal{D} for complementary fine-tuning while \mathcal{D}'_t (t^{th} partition of \mathcal{D}) for complementary+efficient fine-tuning. \oplus : addition; \odot : Hadamard product; \oplus : concatenation; Green dashed lines: variational component of NVDM.

In Figure 1, we run BERT for different sequence lengths (32, 64, 128, 256 and 512) with batch-size=4 to estimate GPU-memory consumed and CO_2 using equation 1. We run each model for 15 epochs and compute run-time (in hours).

For Table 1, we estimate CO_2 for document classification tasks (BERT fine-tuning) considering 512 sequence length. We first estimate the total BERT fine-tuning time in terms of research activities and/or its applications beyond using multiple factors. Then, using equation 1 the final CO_2 is computed. (See *supplementary* for detailed computation)

2 Methodology: TopicBERT

Figure 2 illustrates the architecture of *TopicBERT* consisting of: (1) Neural Topic Model (NTM), (2) Neural Language Model (NLM) to achieve complementary and efficient document understanding.

2.1 TopicBERT: Complementary Fine-tuning

Given a document $\mathcal{D} = [w_1, ..., w_N]$ of sequence length N, consider $\mathbf{V} \in \mathbb{R}^Z$ be its BoW representation, $\mathbf{v_i} \in \mathbb{R}^Z$ be the one-hot representation of the word at position i and Z be the vocabulary size.

The **Neural Topic Model** component (Figure 2, left) is based on Neural Variational Document Model (NVDM) (Miao et al., 2016), seen as a variational autoencoder for document modeling in an unsupervised generative fashion such that:

¹https://mlco2.github.io/impact/

(a) an MLP encoder f^{MLP} and two linear projections l_1 and l_2 compress the input document \mathbf{V} into a continuous hidden vector $\mathbf{h}_{TM} \in \mathbb{R}^K$:

$$\begin{split} & \boldsymbol{\pi} = g(\boldsymbol{f}^{MLP}(\mathbf{V})) \ \text{ and } \ \boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I}) \\ & \boldsymbol{\mu}(\mathbf{V}) = l_1(\boldsymbol{\pi}) \qquad \text{and } \ \boldsymbol{\sigma}(\mathbf{V}) = l_2(\boldsymbol{\pi}) \\ & q(\mathbf{h}_{TM}|\mathbf{V}) = \mathcal{N}(\mathbf{h}_{TM}|\boldsymbol{\mu}(\mathbf{V}), \operatorname{diag}(\boldsymbol{\sigma}(\mathbf{V}))) \\ & \mathbf{h}_{TM} \sim q(\mathbf{h}_{TM}|\mathbf{V}) \implies \mathbf{h}_{TM} = \boldsymbol{\mu}(\mathbf{V}) \oplus \boldsymbol{\epsilon} \odot \boldsymbol{\sigma}(\mathbf{V}) \end{split}$$

The \mathbf{h}_{TM} is sampled from a posterior distribution $q(\mathbf{h}_{TM}|\mathbf{V})$ that is parameterized by mean $\mu(\mathbf{V})$ and variance $\sigma(\mathbf{V})$, generated by neural network. We call \mathbf{h}_{TM} as a *document-topic-representation* (DTR), summarizing document semantics.

(b) a softmax $decoder \hat{\mathbf{V}}$, i.e, $p(\mathbf{V}|\mathbf{h}_{TM}) = \prod_{i=1}^{N} p(\mathbf{v_i}|\mathbf{h}_{TM})$ reconstructs the input document \mathbf{V} by generating all words $\{\mathbf{v_i}\}$ independently:

$$\begin{split} p(\mathbf{v_i}|\mathbf{h}_{TM}) &= \frac{\exp\{\mathbf{h}_{TM}^T\mathbf{U}_{:,i} + \mathbf{c_i}\}}{\sum_{j=1}^Z \exp\{\mathbf{h}_{TM}^T\mathbf{U}_{:,i} + \mathbf{c_i}\}} \\ \mathcal{L}_{NVDM} &= \mathbb{E}_{q(\mathbf{h}_{TM}|\mathbf{V})}\big[\log p(\mathbf{V}|\mathbf{h}_{TM})\big] - \text{KLD} \end{split}$$

where $\mathbf{U} \in \mathbb{R}^{K \times Z}$ and $\mathbf{c} \in \mathbb{R}^{Z}$ are decoding parameters, \mathcal{L}_{NVDM} is the lower bound, i.e., $\log p(\mathbf{V}) \geqslant \mathcal{L}_{NVDM}$ and KLD = KL $[q(\mathbf{h}_{TM}|\mathbf{V})||p(\mathbf{h}_{TM})]$ is the KL-Divergence between the Gaussian posterior $q(\mathbf{h}_{TM}|\mathbf{V})$ and prior $p(\mathbf{h}_{TM})$ for \mathbf{h}_{TM} . During training, NVDM maximizes log-likelihood $\log p(\mathbf{V}) = \sum_{\mathbf{h}_{TM}} p(\mathbf{V}|\mathbf{h}_{TM})p(\mathbf{h}_{TM})$ by maximizing \mathcal{L}_{NVDM} using stochastic gradient descent. See further details in Miao et al. (2016).

The **Neural Language Model** component (Figure 2, right) is based on BERT (Devlin et al., 2019). For a document \mathcal{D} of length N, BERT first tokenizes the input sequence into a list of sub-word tokens \mathcal{X} and then performs $O(N^2n_l)$ self-attention operations in n_l encoding layers to compute its contextualized representation $\mathbf{o}_{CLS} \in \mathbb{R}^{H_B}$, extracted via a special token [CLS]. Here, H_B is the number of hidden units. We use \mathbf{o}_{CLS} to fine-tune BERT.

Complementary Learning: TopicBERT (Figure 2) jointly performs neural topic and language modeling in a unified framework, where document-topic \mathbf{h}_{TM} and contextualized \mathbf{o}_{CLS} representations are first concatenated-projected to obtain a topic-aware contextualized representation $\mathbf{h}_p \in \mathbb{R}^{H_B}$ and then \mathbf{h}_p is fed into a classifier:

$$\mathbf{h}_{p} = (\mathbf{h}_{TM} \bigoplus \mathbf{o}_{CLS}) \cdot \mathbf{P}$$

$$p(y = y_{l}|\mathcal{D}) = \frac{\exp\{\mathbf{h}_{p}^{T} \mathbf{Q}_{:,y} + \mathbf{b}_{y}\}}{\sum_{j=1}^{L} \exp\{\mathbf{h}_{p}^{T} \mathbf{Q}_{:,y_{j}} + \mathbf{b}_{y_{j}}\}}$$

$$\mathcal{L}_{TopicBERT} = \alpha \log p(y = y_{l}|\mathcal{D}) + (1 - \alpha)\mathcal{L}_{NVDM}$$

where, $\mathbf{P} \in \mathbb{R}^{\hat{H} \times H_B}$ is the projection matrix, $\hat{H} = H + H_B$, $\mathbf{Q} \in \mathbb{R}^{H_B \times L}$ & $\mathbf{b} \in \mathbb{R}^L$ are classification parameters, $y_l \in \{y_1, ..., y_L\}$ is the true label

	BERT	TopicBERT
Sequence length	N	N/p
Time Complexity (batch-wise)	$b(N^2H_B)n_l$	$bKZ + b(N^2H_B/p^2)n_l$
#Batches	n_b	$p \times n_b$
Time Complexity (epoch-wise)	$b(N^2H_Bn_b)n_l$	$bKZn_b + b(N^2H_Bn_b/p)n_l$

Table 2: Time complexity of BERT vs TopicBERT. Here, b: batch-size, n_b : #batches and n_l : #layers in BERT. Note, the compute cost of NVDM and self-attention operations as $KZ << (N^2H_B/p)n_l$. In TopicBERT: p=1 for complementary learning, and $p=\{2,4,8\}$ for complementary+efficient learning.

for \mathcal{D} and L is the total number of labels. During training, the TopicBERT maximizes the joint objective $\mathcal{L}_{TopicBERT}$ with $\alpha \in (0,1)$. Similarly, we extract o_{CLS} from DistilBERT (Sanh et al., 2019a) and the variant is named as TopicDistilBERT.

2.2 TopicBERT: Efficient Fine-tuning

Since the computation cost of BERT grows quadratically $O(N^2)$ with sequence length N and is limited to 512 tokens, therefore there is a need to deal with larger sequences. The TopicBERT model offers efficient fine-tuning by reducing the number of self-attention operations in the BERT component.

In doing this, we split a document \mathcal{D} into p partitions each denoted by \mathcal{D}' of length N/p. The NVDM component extracts document-topic representation \mathbf{h}_{TM} efficiently for the input \mathcal{D} and BERT extracts contextualized representation \mathbf{o}_{CLS} for \mathcal{D}' , such that the self-attention operations are reduced by a factor of p^2 in each batch while still modeling all cross-partition dependencies within the complementary learning paradigm. Table 2 illustrates the computation complexity of BERT vs TopicBERT and the efficiency achieved.

3 Experimental Results and Analysis

Datasets: For document classification, we use 5 datasets (*Reuter8*, *Imdb*, *20NS*, *Ohsumed*, *AGnews*) from several domains. (See *supplementary* for data descriptions and experimental results of *AGnews*)

Baselines: (a) *CNN* (Kim, 2014), (b) *BERT-Avg*: Logistic classifier over the vector \mathcal{D}_B of a document obtained by averaging its contextualized word embeddings from *BERT*, (c) *BERT-Avg+DTR*: Logistic classifier over concatenation(\mathcal{D}_B , *DTR*) where $DTR = \mathbf{h}_{TM}$ from pre-trained NVDM, i.e., no joint fine-tuning, (d) *DistilBERT* (Sanh et al., 2019b), (e) *BERT* fine-tuned. We compare our ex-

	M. 1.1.	Rei	uters8 (ne	ws dom	ain)		Ime	db (sentim	ent don	nain)	
	Models	F1	Rtn	T_{epoch}	T	CO_2	F1	Rtn	T_{epoch}	T	CO_2
	CNN	0.852 ± 0.000	91.123%	0.007	0.340	14.51	0.884 ± 0.000	94.952%	0.201	2.010	85.83
se	BERT-Avg	0.882 ± 0.000	94.331%	-	0.010	0.47	0.883 ± 0.000	94.844%	-	0.077	3.29
baselines	BERT- $Avg + DTR$	0.867 ± 0.000	92.727%	-	0.015	0.68	0.894 ± 0.000	96.026%	-	0.114	4.87
pa	DistilBERT	0.934 ± 0.003	99.893%	0.129	1.938	82.75	0.910 ± 0.003	97.744%	0.700	10.500	448.35
	BERT	0.935 ± 0.012	100.00%	0.208	3.123	133.34	0.931 ± 0.002	100.00%	0.984	14.755	630.04
	TopicBERT-512	0.950 ± 0.005	101.60%	0.212	3.183	135.93	0.934 ± 0.002	100.32%	1.017	15.251	651.22
proposal	TopicBERT-256	0.942 ± 0.009	100.74%	0.125	1.870	79.85	0.936 ± 0.002	$\underline{100.53}\%$	0.789	11.838	<u>505.46</u>
pro	TopicBERT-128	0.928 ± 0.015	99.251%	<u>0.107</u>	<u>1.610</u>	<u>68.76</u>	0.928 ± 0.002	99.677%	0.890	13.353	570.17
	TopicBERT-64	0.921 ± 0.006	98.502%	0.130	1.956	83.51	0.909 ± 0.015	97.636%	1.164	17.461	745.60
	Gain (performance)	↑ 1.604%					↑ 0.537%	-			
	Gain (efficiency)	-	99.251%	↓1.9 ×	↓1.9 ×	↓1.9 ×	-	100.53%	↓1.2 ×	↓1.2 ×	↓1.2 ×
	20 Newsgroups (20NS) (news domain)										<u> </u>
		20 Newsgi	roups (201	NS) (nev	vs doma	ain)	Ohsi	umed (med	dical do	main)	
		20 Newsgi	roups (201 Rtn	T_{epoch}	vs doma	ain) CO_2	Ohst	umed (med	dical do T_{epoch}	main)	CO_2
_	CNN	U	Rtn	T_{epoch}			I.	Rtn	T_{epoch}		CO ₂ 302.74
lles	CNN BERT-Avg	F1	Rtn 95.504%	T_{epoch}	T	CO_2	F1	Rtn 89.179%	T_{epoch}	T	
selines		$F1$ 0.786 \pm 0.000	Rtn 95.504% 84.083%	$\frac{T_{epoch}}{0.109}$	T 1.751	<i>CO</i> ₂ 74.76	$F1$ 0.684 \pm 0.000	Rtn 89.179% 59.061%	T_{epoch} 0.177	7.090	302.74
baselines	BERT-Avg	$F1 = 0.786 \pm 0.000 \\ 0.692 \pm 0.000$	Rtn 95.504% 84.083% 88.821%	T _{epoch} 0.109 -	T 1.751 0.037 0.051	CO ₂ 74.76 1.58 2.18	$F1 \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000$	Rtn 89.179% 59.061% 70.795%	T _{epoch} 0.177	7.090 0.094 0.191	302.74 4.01 8.16
baselines	BERT-Avg $BERT-Avg + DTR$	$F1$ 0.786 ± 0.000 0.692 ± 0.000 0.731 ± 0.000	Rtn 95.504% 84.083% 88.821% 99.149%	Tepoch 0.109 0.313	<i>T</i> 1.751 0.037 0.051 4.700	74.76 1.58 2.18 200.69	$F1 \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000$	Rtn 89.179% 59.061% 70.795% 97.913%	Tepoch 0.177 0.684	7.090 0.094 0.191 10.267	302.74 4.01 8.16 438.4
_	BERT-Avg BERT-Avg + DTR DistilBERT	$F1$ 0.786 ± 0.000 0.692 ± 0.000 0.731 ± 0.000 0.816 ± 0.005	Rtn 95.504% 84.083% 88.821% 99.149% 100.00%	Tepoch 0.109 - 0.313 0.495	T 1.751 0.037 0.051 4.700 7.430	CO ₂ 74.76 1.58 2.18 200.69 317.28	$F1 \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000 \\ 0.751 \pm 0.006$	Rtn 89.179% 59.061% 70.795% 97.913% 100.00%	T _{epoch} 0.177 0.684 1.096	7.090 0.094 0.191 10.267	302.74 4.01 8.16 438.4 702.07
_	BERT-Avg BERT-Avg + DTR DistilBERT BERT	$FI \\ 0.786 \pm 0.000 \\ 0.692 \pm 0.000 \\ 0.731 \pm 0.000 \\ 0.816 \pm 0.005 \\ 0.823 \pm 0.007$	Rtn 95.504% 84.083% 88.821% 99.149% 100.00% 100.36%	Tepoch 0.109 - 0.313 0.495	T 1.751 0.037 0.051 4.700 7.430	CO ₂ 74.76 1.58 2.18 200.69 317.28 324.76	$FI \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000 \\ 0.751 \pm 0.006 \\ 0.767 \pm 0.002$	Rtn 89.179% 59.061% 70.795% 97.913% 100.00% 100.26%	T _{epoch} 0.177 0.684 1.096 1.069	7.090 0.094 0.191 10.267 16.442	302.74 4.01 8.16 438.4 702.07 684.75
proposal baselines	BERT-Avg BERT-Avg + DTR DistilBERT BERT TopicBERT-512	$FI \\ 0.786 \pm 0.000 \\ 0.692 \pm 0.000 \\ 0.731 \pm 0.000 \\ 0.816 \pm 0.005 \\ 0.823 \pm 0.007 \\ 0.826 \pm 0.004$	Rtm 95.504% 84.083% 88.821% 99.149% 100.00% 100.36% 100.00%	Tepoch 0.109 - 0.313 0.495 0.507 0.400	T 1.751 0.037 0.051 4.700 7.430 7.606 5.993	CO ₂ 74.76 1.58 2.18 200.69 317.28 324.76 255.90	$FI \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000 \\ 0.751 \pm 0.006 \\ 0.767 \pm 0.002 \\ \textbf{0.769} \pm 0.005$	Rtn 89.179% 59.061% 70.795% 97.913% 100.00% 100.26% 99.217%	Tepoch 0.177 0.684 1.096 1.069 0.902	7.090 0.094 0.191 10.267 16.442	302.74 4.01 8.16 438.4 702.07 684.75 <u>577.73</u>
_	BERT-Avg BERT-Avg + DTR DistilBERT BERT TopicBERT-512 TopicBERT-256	$FI \\ 0.786 \pm 0.000 \\ 0.692 \pm 0.000 \\ 0.731 \pm 0.000 \\ 0.816 \pm 0.005 \\ 0.823 \pm 0.007 \\ 0.826 \pm 0.004 \\ 0.823 \pm 0.016 \\ 0.826 \pm 0.004$	Rtn 95.504% 84.083% 88.821% 99.149% 100.00% 100.36% 100.36%	Tepoch 0.109 - 0.313 0.495 0.507 0.400 0.444	T 1.751 0.037 0.051 4.700 7.430 7.606 5.993 6.666	74.76 1.58 2.18 200.69 317.28 324.76 255.90 284.64	$FI \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000 \\ 0.751 \pm 0.006 \\ 0.767 \pm 0.002 \\ \textbf{0.769} \pm 0.005 \\ 0.761 \pm 0.001$	Rtn 89.179% 59.061% 70.795% 97.913% 100.00% 100.26% 99.217% 96.349%	Tepoch 0.177 0.684 1.096 1.069 0.902 1.003	7.090 0.094 0.191 10.267 16.442 16.036 <u>13.530</u> 15.047	302.74 4.01 8.16 438.4 702.07 684.75 <u>577.73</u> 642.50
_	BERT-Avg BERT-Avg + DTR DistilBERT BERT TopicBERT-512 TopicBERT-256 TopicBERT-128	$FI \\ 0.786 \pm 0.000 \\ 0.692 \pm 0.000 \\ 0.731 \pm 0.000 \\ 0.816 \pm 0.005 \\ 0.823 \pm 0.007 \\ 0.826 \pm 0.004 \\ 0.823 \pm 0.016 \\ 0.826 \pm 0.004 \\ 0.830 \pm 0.002$	Rtn 95.504% 84.083% 88.821% 99.149% 100.00% 100.36% 100.36%	Tepoch 0.109 - 0.313 0.495 0.507 0.400 0.444	T 1.751 0.037 0.051 4.700 7.430 7.606 5.993 6.666	74.76 1.58 2.18 200.69 317.28 324.76 255.90 284.64	$FI \\ 0.684 \pm 0.000 \\ 0.453 \pm 0.000 \\ 0.543 \pm 0.000 \\ 0.751 \pm 0.006 \\ 0.767 \pm 0.002 \\ \textbf{0.769} \pm 0.005 \\ 0.761 \pm 0.001 \\ 0.739 \pm 0.006$	Rtn 89.179% 59.061% 70.795% 97.913% 100.00% 100.26% 99.217% 96.349%	Tepoch 0.177 0.684 1.096 1.069 0.902 1.003	7.090 0.094 0.191 10.267 16.442 16.036 <u>13.530</u> 15.047	302.74 4.01 8.16 438.4 702.07 684.75 <u>577.73</u> 642.50

Table 3: TopicBERT for document classification (macro-F1). Rtn: Retention in F1 vs BERT; T_{epoch} : average epoch time (in hours); T: $T_{epoch} \times 15$ epochs; CO_2 : Carbon in $gram\ eq$. (equation 1); **bold**: Best (fine-tuned BERT-variant) in column; <u>underlined</u>: Most efficient TopicBERT-x vs BERT; Gain (performance): TopicBERT-x vs TopicBERT-

tensions as: *TopicBERT* vs *BERT* (below) and *Top-icDistilBERT* vs *DistilBERT* (in *supplementary*).

Experimental setup: For BERT component, we split the input sequence \mathcal{D} into p equal partitions each of length $x = N_B/p$, where $N_B = 512$ (due to token limit of *BERT*) and $p \in \{1, 2, 4, 8\}$ (a hyperparameter of *TopicBERT*). To avoid padding in the last partition, we take the last x tokens of \mathcal{D} . We run TopicBERT-x (i.e., BERT component) for different sequence length (x) settings, where (a) p=1, i.e., TopicBERT-512 denotes complementary finetuning, and (b) $p \in \{2, 4, 8\}$, i.e., TopicBERT- $\{256, 6, 10\}$ 128, 64} denotes complementary+efficient finetuning. Note, NVDM always considers the fullsequence. We execute 3 runs of each experiment on an NVIDIA Tesla T4 16 GB Processor to a maximum of 15 epochs. Carbon footprint (CO_2) is computed as per equation 1. (See supplementary for hyperparameters)

Results: Table 3 illustrates gains in *performance* and *efficiency* of *TopicBERT*, respectively due to complementary and efficient fine-tuning. E.g. in Reuters8, *TopicBERT-512* achieves a gain of 1.6%

in F1 over BERT and also outperforms DistilBERT. In the efficient setup, TopicBERT-128 achieves a significant speedup of $1.9 \times (1.9 \times \text{ reduction in } CO_2)$ in fine-tuning while retaining (Rtn) 99.25% of F1 of BERT. For IMDB and 20NS, TopicBERT-256 reports similar performance to BERT, however with a speedup of $1.2 \times$ and also outperforms Distil-BERT in F1 though consuming similar time T_{epoch} . Additionally, TopicBERT-512 exceeds DistilBERT in F1 for all the datasets. At p=8, TopicBERT-64 does not achieve expected efficiency perhaps due to saturated GPU-parallelization (a trade-off in decreasing sequence length and increasing #batches).

Overall, *TopicBERT-x* achieves gains in: (a) performance: 1.604%, 0.850%, 0.537%, 0.260% and 0.319% in F1 for Reuters8, 20NS, IMDB, Ohsumed and AGnews (in supplementary), respectively, and (b) efficiency: a speedup of $1.4\times$ (\sim 40%) and thus, a reduction of \sim 40% in CO_2 over 5 datasets while retaining 99.9% of F1 compared to BERT. It suggests that the topical semantics improves document classification in TopicBERT (and TopicDistilBERT: a further 1.55x speedup in Distil-

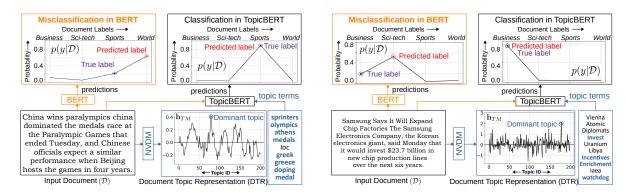


Figure 3: Interpretability analysis of document classification for AGnews dataset (for 2 different input documents): Illustration of document misclassification by *BERT* and correct classification by *TopicBERT* explained by the top key terms of dominant topic in DTR.

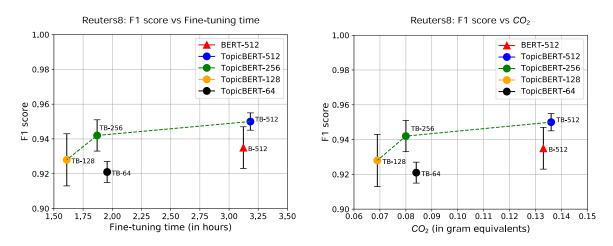


Figure 4: Pareto frontier analysis for Reuters8 dataset: F1 score vs Fine-tuning time (left) and F1 score vs CO_2 (carbon footprint) (right). Here green dashed line represents Pareto frontier connecting optimal solutions

BERT) and its energy-efficient variants.

Analysis (Interpretability): For two different input documents, Figure 3 illustrates the misclassification by BERT and correct classification with explanation by TopicBERT, suggesting that the DTR (\mathbf{h}_{TM} of NVDM) improves document understanding. The TopicBERT extracts key terms of the dominant topic (out of 200) discovered by the NVDM component for each document. Observe that the topic terms explain the correct classification in each case. (See supplementary for additional details and examples)

Analysis (Pareto Frontier): As shown in Table 3, gains in *TopicBERT* has been analyzed on two different fronts: (a) gain on the basis of *performance* (F1 score), and (b) gain on the basis of *efficiency* (Fine-tuning time/ CO_2). Figure 4 illustrates the following Pareto frontier analysis plots for Reuters8 dataset: (a) F1 score vs Fine-tuning time (left), and (b) F1 score vs CO_2 (right) to find the optimal solution that balances both fronts. Ob-

serve that the TopicBERT-512 outperforms all other TopicBERT variants and BERT baseline (B-512) in terms of performance i.e., F1 score. However, TopicBERT-256 outperforms BERT-512 in terms of both, performance (F1 score) and efficiency (Finetuning time/ CO_2). Therefore, TopicBERT-256 represents the optimal solution with optimal sequence length of 256 for Reuters8 dataset.

4 Conclusion

We have presented two novel architectures: Top-icBERT and TopicDistilBERT for an improved and efficient (Fine-tuning time/ CO_2) document classification, leveraging complementary learning of topic (NVDM) and language (BERT) models.

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A Supplementary Material

A.1 CO_2 : Carbon footprint estimation

For Table 1, we estimate CO₂ for document classification tasks (BERT fine-tuning) considering 512 sequence length. We first estimate the frequency of BERT fine-tuning in terms of research activities and/or its application beyond. We estimate the following items:

- 1. Number of scientific papers based on BERT = 5532 (number of BERT citations to date: 01, June 2020)
- 2. Conference acceptance rate: 25% (i.e., 4 times the original number of submissions or research/application beyond the submissions)
 - 3. Average number of datasets used = 5
- 4. Average run-time of 15 epochs in fine-tuning BERT over 5000 documents (Reusters8-sized data) of maximum 512 sequence length = 12 hours on the hardware-type used

Therefore, using equation 1 in main paper,

 CO_2 estimate in fine-tuning BERT = 0.07 × (5532 × 4 × 5) × 12 × 0.61 kg eq. = 56,692 × 2,20462 lbs eq = 124,985 lbs eq.

A.2 Data statistics and preprocessing

Table 4 shows data statistics of 5 datasets used in complementary + finetuning evaluation of our proposed TopicBERT model via Document Classification task. 20Newsgroups (20NS), Reuters8, AGnews are *news* domain datasets, whereas Imdb and Ohsumed datasets belong to *sentiment* and *medical* domains respectively. For NVDM component, we preprocess each dataset and extract vocabulary Z as follows: (a) tokenize documents into words, (b) lowercase all words, (d) remove stop words², and

	Train	Dev	Test				
Dataset	#docs	#docs	#docs	Z	L	N	b
Reuters8	4.9k	0.5k	2.1k	4813	8	512	4
Imdb	20k	5k	25k	6823	2	512	4
20NS	9.9k	1k	7.4k	4138	20	512	4
AGNews	118k	2k	7.6k	5001	4	128	32
$Ohsumed^{\dagger}$	24k	3k	2.9k	4553	20	512	4

Table 4: Preprocessed data statistics: **#docs** \rightarrow number of documents, k \rightarrow thousand, Z \rightarrow vocabulary size of NVDM, L \rightarrow total number of unique labels, N \rightarrow sequence length used for *BERT* fine-tuning, b \rightarrow batch-size used for BERT fine-tuning, (†) \rightarrow multi-labeled dataset

(c) remove words with frequency less than F_{min} . Here, $F_{min}=100$ for large datasets i.e., Imdb, 20NS, AGnews and Ohsumed, whereas $F_{min}=10$ for Reuters8 which is a small dataset.

Hyperparameter	Value(s)
Learning rate	<u>0.001</u> , 0.05
Hidden size (H)	<u>256</u> , 128
Batch size (b)	4, 32
Non-linearity (g)	sigmoid
Sampling	5, 10
frequency of \mathbf{h}_{TM}	J, <u>10</u>
Number of	50, 100,200
topics (K)	30, <u>100,</u> 200

Table 5: Hyperparameters search and optimal settings for NVDM component of *TopicBERT* used in the experimental setup for document classification task.

A.3 Experimental setup

Table 5 and 7 shows hyperparameter settings of NVDM and BERT components of our proposed *TopicBERT* model for document classification task. We initialize BERT component with pretrained BERT-base model released by Devlin et al. (2019). Fine-tuning of *TopicBERT* is performed as follows: (1) perform pretraining of NVDM component, (2) initialize *BERT* component with BERT-base model, (3) perform complementary + efficient fine-tuning, for 15 epochs, using joint loss objective:

 $\mathcal{L}_{TopicBERT} = \alpha \log p(y=y_l|\mathcal{D}) + (1-\alpha)\mathcal{L}_{NVDM}$ where, $\alpha \in \{0.1, 0.5, 0.9\}$. For CNN, we follow the experimental setup of Kim (2014).

A.4 Results of TopicBERT for AGnews

Table 8 shows gains in *performance* and *efficiency* of *TopicBERT* vs *BERT* for AGnews dataset. *TopicBERT* achieves: (a) a gain of 0.3% in *F1* (*perfor-*

²we use NLTK tool to remove stopwords

	Models	Reu	Reuters8 (news domain)				20NS (news domain)				
	Wiodels	F1	Rtn	T_{epoch}	T	CO_2	F1	Rtn	T_{epoch}	T	CO_2
aselines	CNN	0.852 ± 0.000	91.123%	0.007	0.340	14.51	0.786 ± 0.000	95.504%	0.109	1.751	74.76
base	DistilBERT	0.934 ± 0.003	100.00%	0.129	1.938	82.75	0.816 ± 0.005	100.000%	0.313	4.700	200.69
osal	TopicDistilBERT-512	0.941 ± 0.007	100.75%	0.132	1.976	84.37	0.820 ± 0.000	100.49%	0.320	4.810	205.38
propo	$Topic Distil BERT \hbox{-} 256$	0.943 ± 0.006	$\underline{100.96}\%$	0.085	<u>1.272</u>	<u>54.31</u>	0.802 ± 0.000	98.284%	<u>0.190</u>	<u>2.850</u>	<u>121.69</u>
ā	Topic Distil BERT-128	0.911 ± 0.012	97.573%	0.096	1.444	61.66	0.797 ± 0.000	97.671%	0.387	5.800	247.66
	Gain (performance)	↑ 0.964%		-	-		↑ 0.490 %		-	-	-
	Gain (efficiency)	-	100.96%	↓1.5 ×	↓1.5 ×	↓1.5 ×	-	98.284%	↓1.6 ×	↓1.6 ×	↓1.6 ×

Table 6: TopicDistilBERT vs DistilBERT for document classification (macro-F1) in complementary (TopicDistilBERT-512) and efficient (TopicDistilBERT-{256, 128}) learning setup. Here, Rtn: Retention in F1 vs BERT; T_{epoch} : average epoch time (in hours); T: $T_{epoch} \times 15$ epochs; CO_2 : Carbon footprint in $gram\ eq$. (equation 1); **bold**: Best (fine-tuned DistilBERT-variant) in column; <u>underlined</u>: Most efficient TopicDistilBERT-Top

Hyperparameter	Value(s)
Learning rate*	2e-5
Hidden size (H_B)	768
Batch size (b)	[4, 32]
Non-linearity*	gelu
Maximum sequence	[512, 256,
length(N)	128, 64, 32 [‡]]
Number of	10
attention heads*	12
Number of	10
encoder layers* (n_l)	12
Vocabulary size*	28996
Dropout probability*	0.1
α	$[0.1, 0.5, \underline{0.9}]$

Table 7: Hyperparameters search and optimal settings for BERT component of TopicBERT used in the experimental setup for document classification. $^{\dagger} \rightarrow$ additional hyperparameter introduced for joint modeling in TopicBERT, $^{\dagger} \rightarrow N = 32$ is only used for AGnews dataset, (*) \rightarrow hyperparameter values taken from pretrained BERT-base model released by Devlin et al. (2019).

mance) compared to BERT, and (b) a significant speedup of $1.3 \times$ over BERT while retaining (Rtn) 100% of F1 (performance) of BERT at the same time. This gain arises due to the improved document understanding using complementary topical semantics, via NVDM, in TopicBERT and its energy efficient versions.

A.5 TopicDistilBERT vs DistilBERT

Table 6 reports scores of *TopicDistilBERT* vs *DistilBERT* for two datasets (Reuters8 and 20NS). We follow the similar schemes of sequence

	Models	AGnews					
	Models	F1	Rtn	T_{epoch}	T	CO_2	
	CNN	0.916 ± 0.000	97.447%	0.131	0.921	393.25	
səu	BERT-Avg	0.903 ± 0.000	96.064%	-	0.075	3.20	
baselines	BERT- $Avg + DTR$	0.913 ± 0.000	97.128%	-	0.105	4.48	
ğ	DistilBERT-x	0.941 ± 0.001	100.10%	0.491	7.361	314.31	
	BERT-x	0.940 ± 0.001	100.00%	0.952	14.281	609.80	
sal	TopicBERT-128	0.942 ± 0.003	100.21%	1.004	15.065	643.27	
proposal	TopicBERT-64	0.943 ± 0.002	$\underline{100.31\%}$	0.723	10.838	<u>462.78</u>	
<u> </u>	TopicBERT-32	0.938 ± 0.001	99.78%	0.846	12.688	541.66	
	Gain (performance)	↑ 0.319 %		-	-	-	
	Gain (efficiency)	-	100.31%	↓ 1.3 ×	↓ 1.3 ×	↓ 1.3 ×	

Table 8: TopicBERT for document classification (macro-F1) for AGnews dataset. Rtn: Retention in F1 vs BERT; T_{epoch} : average epoch time (in hours); T: $T_{epoch} \times 15$ epochs; CO_2 : Carbon footprint in gram eq. (equation 1); **bold**: Best (fine-tuned BERT-variant) in column; <u>underlined</u>: Most efficient TopicBERT-x vs BERT; Gain (performance): TopicBERT-x vs T

lengths (512, 256 and 128) to evaluate the performance of the (a) complementary learning via *TopicDistilBERT-512* vs *DistilBERT*, and (b) efficient learning via *TopicDistilBERT-*{256, 128} vs *DistilBERT*.

For Reuters8 in complementary setup, TopicDistilBERT-512 achieves a gain (0.941 vs 0.934) in F1 over DistilBERT. In the efficient setup, TopicDistilBERT-256 achieves a significant speedup of $1.5 \times (1.5 \times, \text{ i.e., } \sim 50\%$ reduction in CO_2) in fine-tuning while retaining (Rtn) 100.96% of F1 of DistilBERT.

For 20NS in complementary setup, TopicDistilBERT-512 achieves a gain (0.820 vs 0.816) in F1 over DistilBERT. In the efficient setup, TopicDistilBERT-256 achieves a speedup of $1.6 \times (1.6 \times, \text{i.e.}, \sim 60\% \text{ reduction in CO}_2)$.

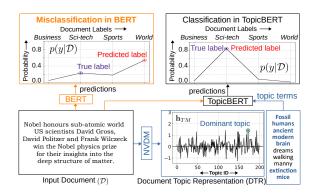


Figure 5: Interpretability analysis of document classification for AGnews dataset (for 2 input documents): Illustration of document misclassification by *BERT* model and correct classification by *TopicBERT* explained by the top key terms of dominant topic in DTR.

Additionally, TopicBERT-512 exceeds Distil-BERT in F1 for the two datasets. At p=4, TopicDistilBERT-128 does not achieve expected efficiency perhaps due to saturated GPU-parallelization (a trade-off in decreasing sequence length and increasing #batches) and therefore, we do not partition further.

Overall, *TopicDistilBERT-x* achieves gains in: (a) *performance*: 0.964%, and 0.490% in F1 for Reuters8 and 20NS, respectively, and (b) *efficiency*: a speedup of $1.55 \times (\sim 55\%)$ and thus, a reduction of $\sim 55\%$ in CO₂ over 2 datasets while retaining 99.6% of F1 compared to *DistilBERT* baseline model.

It suggests that the topical semantics improves document classification in *TopicDistilBERT* (and *TopicBERT*) and its energy-efficient variants. Based on our two extensions: *TopicBERT* and *TopicDistilBERT*, we assert that our proposed approaches of complementary learning (fine-tuning) are *model agnostic* of BERT models.

A.6 Interpretability Analysis in TopicBERT

To analyze the gain in *performance* (F1 score) of *TopicBERT* vs *BERT*, Figure 5 shows document label misclassifications due to *BERT* model. However, *TopicBERT* model is able to correctly predict the labels using document topic representation (DTR) which explains the correct predictions by the top key terms of the dominant topic discovered.