Rebuttal Response

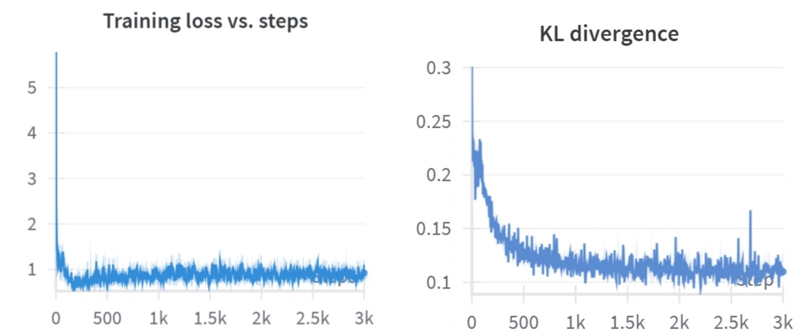

Figure 1. The evolution of the lower-level training loss and KL divergence in training of 10B tokens. Proxy model size: 31M, target LLM size: 410M.

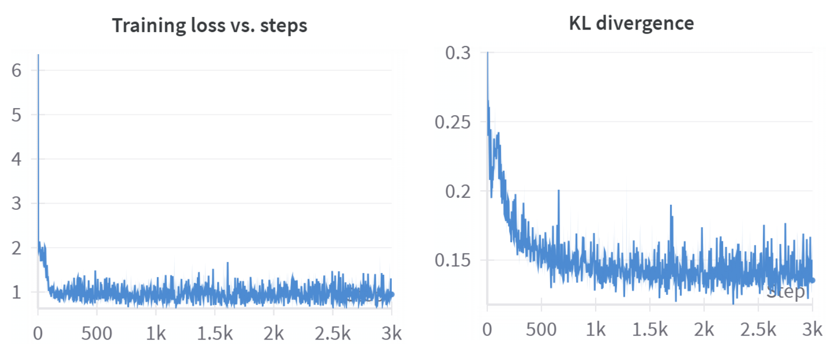

Figure 2. The evolution of the lower-level training loss and KL divergence in training of 10B tokens. Proxy model size: 160M, target LLM size: 410M.

Table 1. Total FLOPs for pretraining 410M/1B target model with 25B tokens.

Process	**#FLOPs** $\times 10^{19}$	**Ratio**
BLISS: 410M model, 25B tokens		
Model pretraining	6.35	79.28%
Warm up the proxy/score model	0.07	0.87%
Bilevel optimization	0.13	1.62%
Data influence model inference	1.53	19.10%
Total	8.08	100.00%
BLISS: 1B model, 25B tokens		
Model pretraining	17.67	90.48%
Warm up the proxy/score model	0.07	0.36%
Bilevel optimization	0.261	1.34%
Data influence model inference	1.53	7.83%
Total	19.53	100.00%

Table 2. Comparison of BLISS with different size of proxy/score model and on zero-shot evaluation over multiuple downstream datasets (410M model, 10B tokens) with 20k-step training.

Method	SciQ	ARC-E	ARC-C	LogiQA	OBQA	BoolQ	HellaSwag	PIQA	WinoGrande	Average
BLISS (Pythia-31M)	65.5(1.5)	40.8(1.0)	23.4(1.2)	27.2(1.7)	29.8(2.0)	58.9(0.9)	36.0(0.5)	67.6(1.1)	53.4(1.4)	44.7(1.3)
BLISS (Pythia-160M)	63.8(1.5)	40.8(1.0)	23.4(1.2)	27.5(1.8)	29.8(2.0)	51.3(0.9)	38.3(0.5)	67.6(1.1)	50.4(1.4)	44.1(1.3)
BLISS (Pythia-31M without sigmoid)	62.6(1.5)	41.0(1.0)	24.0(1.2)	26.4(1.7)	30.4(2.1)	53.4(0.9)	39.5(0.5)	68.3(1.1)	52.2(1.4)	44.2(1.3)

Table 3. Comparison of methods on zero-shot evaluation over multiple downstream datasets (410M model, 15B tokens). BLISS-org denotes the original algorithm, and BLISS† is a variant which uses different initialization method for the score model.

Methods	SciQ	ARC-E	ARC-C	LogiQA	OBQA	BoolQ	HellaSwag	PIQA	WinoGrande	Average
BLISS-org	67.7 (1.5)	41.7 (1.0)	23.6 (1.2)	25.8(1.7)	28.4(2.0)	56.0 (0.8)	39.7 (0.5)	68.7 (1.1)	53.2 (1.4)	44.9 (1.3)
BLISS†	65.2 (1.5)	41.6 (1.0)	23.4 (1.2)	27.1 (1.7)	29.8 (2.0)	57.5 (0.8)	34.9 (0.5)	67.7 (1.1)	53.5 (1.4)	44.5 (1.3)

Table 4. Comparison of methods on zero-shot evaluation over multiple downstream datasets (1B model). BLISS requires much fewer FLOPs to surpass MATES.

Methods (#FLOPs $\times 10^{19}$)	SciQ	ARC-E	ARC-C	LogiQA	OBQA	BoolQ	HellaSwag	PIQA	WinoGrande	Average
MATES (19.97)	67.3 (1.5)	**44.9** (1.0)	**25.9** (1.3)	**28.7**(1.8)	32.2(2.1)	**60.9** (0.9)	45.3 (0.5)	69.5 (1.1)	52.4 (1.4)	47.5 (1.4)
BLISS (11.75)	**70.1 (1.4)**	44.7 (1.0)	24.5 (1.3)	26.7 (1.7)	**33.2 (2.1)**	58.2 (0.9)	**46.6 (0.5)**	**71.8 (1.1)**	**52.5 (1.4)**	**47.6 (1.3)**

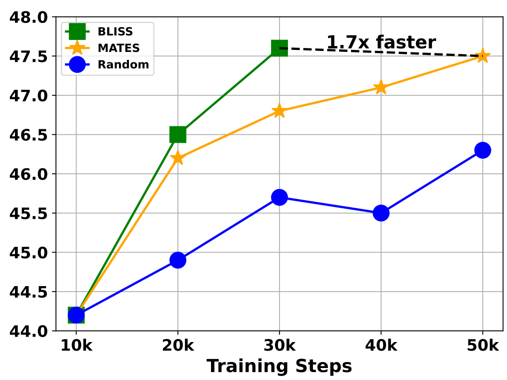

Figure 3. The downstream performance of Pythia-1B model w.r.t. pretrainging steps, where the first point denotes the performance of a warm-up model trained on the randomly selected training data. BLISS achieves an average downstream task performance of 47.6 at 30k pretraining steps, surpassing MATES's performance of 47.5 at 50k pretraining steps. Therefore, BLISS attains a 1.7$\times$ acceleration