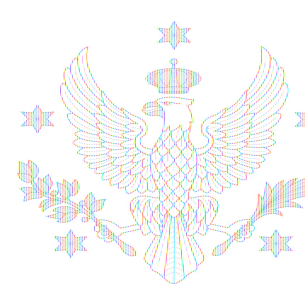


Projected Compression: Trainable Projection for Efficient Transformer Compression

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TL;DR

We introduce **Projected Compression (PC)**, a method for reducing Transformer model size using trainable projections. It preserves access to original weights during training and merges them into a compact form **without increasing per-token FLOPs**. The approach **outperforms hard pruning with retraining (HPR)**, especially at high compression rates.

Projected Compression

Figure 1: Illustration of a PC module, where **P₁** and **P₂** are **projection matrices**, **W** is a **frozen base model parameters** and **W_c** is compressed weights matrix.

Training Loss

Method	Tokens processed during training			
	1B	2B	4B	6B
90% compression				
HPR	3.3870	3.2198	3.1032	3.0500
PC	3.3155	3.1787	3.0809	3.0366
70% compression				
HPR	2.9542	2.8546	2.7767	2.7370
PC	2.9387	2.8439	2.7700	2.7310
50% compression				
HPR	2.7960	2.7005	2.6451	2.6134
PC	2.7986	2.7038	2.6476	2.6154
50% compression with dataset alignment				
HPR	2.7644	2.6966	2.6495	2.6223
PC	2.7656	2.6978	2.6493	2.6216

Table 1: **PC vs HPR** - cross-entropy **loss** of **Llama3 1B compressed** model. **Best** loss from each method pair is **bolded**.

Cost-free projections optimization

Forward and backward passes over tokens run **through the compressed matrix W_c**, not the **P₁, W** and **P₂**. Gradients accumulate in the small parameter space of W_c, then are used to calculate gradients for P₁, P₂ via W.

There are two costs for each training step:

- **Fixed costs** that do not scale with number of tokens in batch: building $W_c = P_1 W P_2$, calculating ∇P_1 , ∇P_2 from ∇W_c .
- **Costs that scales with the number of tokens processed in the batch**: forward and backward cost through W_c to calculate ∇W_c which (step).

With sufficiently **large batch size**, projection optimization costs becomes negligible. Consequently, the total **cost per training step** is **nearly equivalent to** that of retraining a compressed **transformer model** obtained by hard pruning.

It should be noted that PC comes at the expense of additional memory usage that can be mitigated with CPU RAM offloading.

Downstream tasks

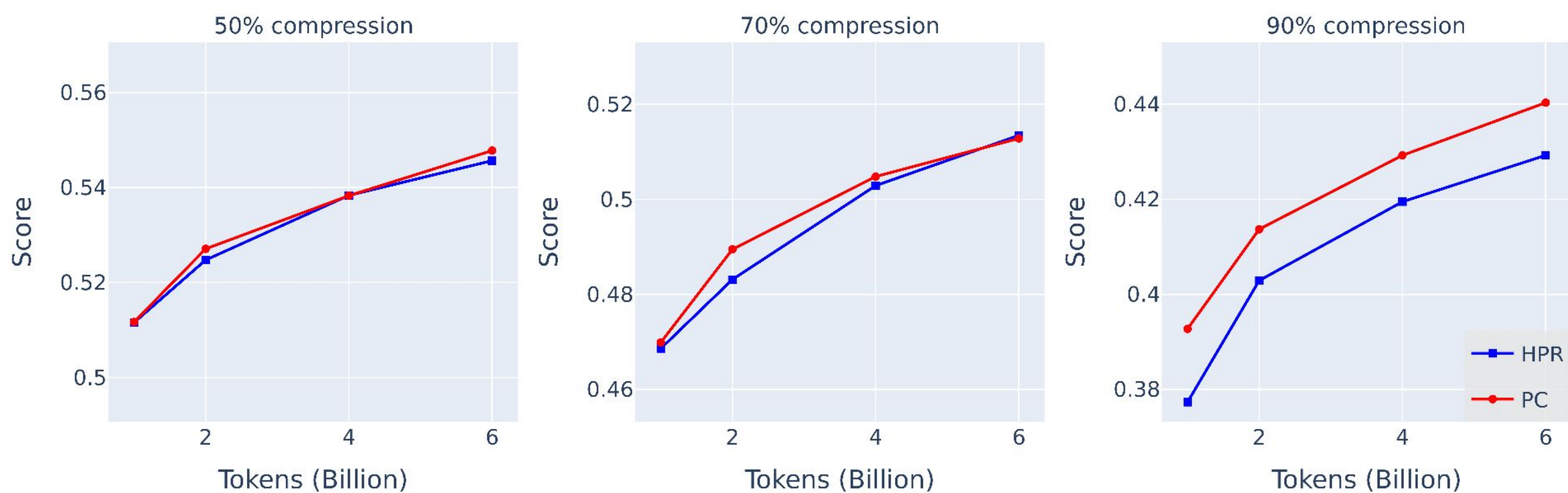


Figure 2: **PC vs HPR** - Averaged **benchmarks** for **compressed Llama3 1B** model. Each data point is obtained from a separate training run.

Full Paper



LLMRandom Nano Framework