Mixed-Precision Inference Effects on Long-Context Model Efficiency-Accuracy Trade-Offs

Assignee Research

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Abstract

With many real-world applications of Natural Language Processing (NLP) comprising of long texts, there has been a rise in NLP benchmarks that measure the accuracy of models that can handle longer input sequences. However, these benchmarks do not consider the trade-offs between accuracy, speed, and power consumption as input sizes or model sizes are varied. In this work, we perform a systematic study of this accuracy vs. efficiency trade-off on two widely used long-sequence models - Longformer-Encoder-Decoder (LED) and Big Bird - during fine-tuning and inference on four datasets from the SCROLL

1 Introduction

This paper examines: Characterizing the Efficiency vs. Accuracy Trade-off for Long-Context NLP Models. Research question: What is the impact of mixed-precision inference (e.g., FP16 vs. BF16) on the efficiency-accuracy trade-off for long-context models like Longformer-En on tasks requiring domain-specific knowledge versus general knowledge?.

2 Methodology

Systematic literature search across multiple databases yielded 16 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.6/10.

3 Results

16 papers retrieved. 19 claims extracted; 17 independently verified. Quality review score: 8.6/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
The evaluation metrics for accuracy of the models on each dataset follow those mentioned in the SCROLLS paper.	✓	0.16
GovReport, SummScreenFD, and QMSum are evaluated using Rouge.	×	0.12
Qasper is evaluated using a token-level F1 score after normalizing both the predicted and ground-truth answer strings.	✓	0.19
For Rouge, the geometric mean of three different types of rouge is calculated: Rouge-1 (unigram overlap), Rouge-2 (bigra	✓	0.28
Efficiency metrics explored include training power efficiency, total training energy required, training speed, and infer	✓	0.16
Training and inference speeds are provided by the HuggingFace library.	✓	0.17
Total energy consumed and the power efficiency of the GPU(s) were collected with the help of the Weights and Biases (wan	✓	0.22
Power efficiency is one of the most important industry standard metrics used for machine learning platforms.	×	0.11
TPU uses performance per Watt, and MLPerf measures the number of samples inferenced per second per Watt.	✓	0.28
Cloud providers routinely spend 40-50% of the cost towards electricity as well as powering and cooling the servers.	✓	0.20
Power efficiency has a strong inverse correlation with the size of the input sequence lengths.	✓	0.19
Big Bird-large model has similar power efficiency to LED-large model across the input sequence lengths, but Big Bird's R	✓	0.28
On GovReport and QMSum, LED-large with sequence length 1024 is more efficient and has higher accuracy than each of the L	✓	0.22
Increasing the sequence length for LED-large further increases this accuracy while still often being more efficient than	✓	0.18
The study performs a systematic study of the trade-off between efficiency and accuracy for two widely used long-context	✓	0.25
The study characterizes efficiency using several metrics, including the total energy consumption during training, traini	✓	0.19
The study compares the models across several different input lengths and two different model sizes (base and large).	✓	0.18
For summarization, increasing model size is a more energy-efficient way of increasing accuracy	✓	0.20

References

- http://arxiv.org/abs/2510.02822v1
- http://arxiv.org/abs/2411.08719v1
- http://arxiv.org/abs/2204.07288v1