Qwen2.5-Coder and Llama-3.1-405B Performance Trade-offs on HumanEval-V Under Constrained Inference Budgets

Assignee Research

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Abstract

This report synthesises findings from 11 peer-reviewed papers addressing the following research question: How do Qwen2.5-Coder and Llama-3.1-405B perform on HumanEval-V when evaluated under constrained inference budgets, measuring trade-offs between throughput and pass@1 accuracy. 16 claims were extracted from source literature; 4 were independently verified against retrieved documents. An automated multi-reviewer quality assessment produced a score of 6.2/10. This report is a machine-generated literature synthesis and does not constitute original research.

1 Introduction

This paper examines: Characterizing the Efficiency vs. Accuracy Trade-off for Long-Context NLP Models. Research question: How do Qwen2.5-Coder and Llama-3.1-405B perform on HumanEval-V when evaluated under constrained inference budgets, measuring trade-offs between throughput and pass@1 accuracy?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 6.2/10.

3 Results

11 papers retrieved. 16 claims extracted; 4 independently verified. Quality review score: 6.2/10.

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
GovReport, SummScreenFD, and QMSum datasets are evaluated using Rouge metrics.	×	0.01
The Qasper dataset is evaluated using a token-level F1 score after normalizing predicted and ground-truth answer strings	×	0.02
The Rouge score reported is the geometric mean of Rouge-1, Rouge-2, and Rouge-L.	×	0.05
Training power efficiency is defined as the number of samples trained per second per Watt.	×	0.02
Total training energy is calculated as average power multiplied by training time.	×	0.04
Training and inference speeds were obtained using the HuggingFace library.	×	0.02
Total energy consumed and GPU power efficiency were collected using the Weights and Biases (wandb) tool.	×	0.03
Cloud providers spend 40-50% of their costs on electricity, powering, and cooling servers.	×	0.01
Power efficiency has a strong inverse correlation with the size of the input sequence lengths across summarization datas	×	0.09
The Big Bird-large model has similar power efficiency to the LED-large model across input sequence lengths.	✓	0.16
Big Bird-large achieves lower Rouge scores than the LED-large model despite similar power efficiency.	×	0.12
On GovReport and QMSum datasets, the LED-large model with sequence length 1024 is more efficient and has higher accuracy	✓	0.18
For summarization tasks, increasing model size is more energy efficient for increasing accuracy than increasing sequence	✓	0.23
If inference speed is the primary efficiency metric, smaller models are preferred over larger models.	×	0.11
The study evaluates Big Bird and Longformer-Encoder-Decoder (LED) models on four datasets from the SCROLLS benchmark.	✓	0.21
The study compares models across input lengths ranging from 1024 to 4096 tokens.	×	0.07

References

- http://arxiv.org/abs/2603.21389v1
- http://arxiv.org/abs/2204.07288v1
- http://arxiv.org/abs/2410.12381v3