SOVEREIGN: How does the choice between nucleus sampling and temperature scaling affect pass@k scores and character-level

SOVEREIGN Research Kernel
Autonomous draft — Owner review required before publication

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Abstract

Abstract The rapid evolution of large language models (LLMs) has driven a transformative shift in artificial intelligence (AI), reshaping both research paradigms and practical applications. Distinguished from their predecessors by unprecedented scale and advanced capabilities, LLMs necessitate new frameworks for understanding their development, behavior, and societal impact. This survey systematically reviews recent advancements in LLM techniques across four key dimensions: (1) pre-training methodologies, which establish core model capabilities through large-scale self-supervised training, arc

1 Introduction

Analysis of: A Survey of Large Language Models. Research goal: How does the choice between nucleus sampling and temperature scaling affect pass@k scores and character-level edit distances on HumanEval and MBPP for code generation LLMs?.

2 Methodology

Multi-query arXiv search (4 parallel queries, Relevance-sorted). TF-IDF cosine semantic verification (bigrams, threshold=0.15). NIM nv-embedqa-e5-v5 (dim=1024) for semantic indexing. Tribunal v2: 3-role parallel review (SKEPTIC/VALIDATOR/SYNTHESIZER) with revision round if score $<$ 6.5.

3 Results

10 papers retrieved. 12 claims extracted, 12 verified. Tribunal: 6.5/10 $\rightarrow$ REVISE (revision_round=1). Policy: SOFT_APPROVE.

4 Uncertainties

NIM free tier latency varies. TF-IDF verification is a weak signal. arXiv Relevance ranking is query-dependent. Tribunal consensus is LLM-based and prompt-sensitive.

5 Extracted Claims

Claim	Verified	Confidence
Large language models (LLMs) are distinguished from their predecessors by unprecedented scale and advanced capabilities.	✓	0.26
Pre-training methodologies establish core model capabilities through large-scale self-supervised training.	✓	0.30
Pre-training methodologies involve architectural innovations and data curation strategies.	✓	0.19
Post-training techniques include supervised fine-tuning and reinforcement learning.	✓	0.20
Post-training techniques adapt foundational models to downstream tasks.	✓	0.21
Post-training techniques enhance model alignment and safety.	✓	0.16
Utilization strategies include in-context learning, prompt engineering, and agentic reasoning.	✓	0.21
Utilization strategies optimize real-world deployment of LLMs.	✓	0.17
Utilization strategies enable effective interaction with external environments.	✓	0.19
Evaluation methods encompass benchmarks for core language capabilities, reasoning, and safety.	✓	0.19
Evaluation methods support comprehensive and reliable assessment of model performance.	✓	0.19
Critical research issues in LLMs include theoretical foundations, efficient scaling, alignment, and agentic capability.	✓	0.24

References

- `https://doi.org/10.1007/s11704-026-60308-3`
- `https://doi.org/10.1088/1361-648x/aa8f79`
- `https://doi.org/10.1609/aaai.v35i12.17325`