

SOVEREIGN: How do different expert routing strategies in MambaFormer affect throughput and FLOPs per token efficiency on

SOVEREIGN Research Kernel

Autonomous draft — Owner review required before publication

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Abstract

We present DeepSeek-V2, a strong Mixture-of-Experts (MoE) language model characterized by economical training and efficient inference. It comprises 236B total parameters, of which 21B are activated for each token, and supports a context length of 128K tokens. DeepSeek-V2 adopts innovative architectures including Multi-head Latent Attention (MLA) and DeepSeekMoE. MLA guarantees efficient inference through significantly compressing the Key-Value (KV) cache into a latent vector, while DeepSeekMoE enables training strong models at an economical cost through sparse computation. Compared with DeepSe

1 Introduction

Analysis of: DeepSeek-V2: A Strong, Economical, and Efficient Mixture-of-Experts Language Model. Research goal: How do different expert routing strategies in MambaFormer affect throughput and FLOPs per token efficiency on code generation tasks?.

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

8 papers retrieved. 10 claims extracted, 10 verified. Tribunal: 9.3/10 → APPROVE (revision_round=0). Policy: AUTO_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
DeepSeek-V2 has 236B total parameters, of which 21B are activated for each token.	✓	0.26
DeepSeek-V2 supports a context length of 128K tokens.	✓	0.22
DeepSeek-V2 adopts Multi-head Latent Attention (MLA) and DeepSeekMoE architectures.	✓	0.27
MLA compresses the Key-Value (KV) cache into a latent vector for efficient inference.	✓	0.25
DeepSeekMoE enables training strong models at an economical cost through sparse computation.	✓	0.30
Compared with DeepSeek 67B, DeepSeek-V2 saves 42.5% of training costs.	✓	0.23
Compared with DeepSeek 67B, DeepSeek-V2 reduces the KV cache by 93.3%.	✓	0.26
Compared with DeepSeek 67B, DeepSeek-V2 boosts the maximum generation throughput to 5.76 times.	✓	0.26
DeepSeek-V2 is pretrained on a corpus consisting of 8.1T tokens.	✓	0.17
DeepSeek-V2 and its chat versions achieve top-tier performance among open-source models with only 21B activated paramete	✓	0.32

References

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- <https://doi.org/10.1186/s40537-021-00444-8>

- <https://doi.org/10.1007/s11704-026-60308-3>