

# Dream Diary: Case Study on Diffusion LLM's Arithmetic Behavior

Mechanistic interpretability studies of autoregressive (AR) models are abundant, while studies on diffusion models (DLLM) remain less explored. In this study, we investigate the arithmetic behaviors of Dream-v0-Instruct-7B (Dream)[5].

We evaluate Dream against 5 arithmetic cases with curated prompts[2]: exact fraction (Exact\_P1; *Calculate -104 / -50? Answer:*), exact addition (Exact\_P2; *Calculate -492 + 191? Answer:*), approximated fraction (Approximate\_P1; *In your head, roughly -104 / -50? Answer:*), approximated addition (Approximate\_P2; *Roughly what's -492 + 191? Answer:*) and rounding (Approximate\_P3; *Approximate 1999? Answer:*). We observe a distinct turning point around layer 11 in both activation entropy and spectral entropy, echoing earlier findings of early answer convergence [2], though in our case this occurs later, around 40% of the decoding depth rather than within the first quarter. The entropy patterns are similar between exact-arithmetic cases and approximated-arithmetic cases; Jensen-Shannon divergences [3] measured at each layer also suggest a similar energy distribution between the two cases. The effective rank study [4] shows similar dimensionalities of approximated fraction and approximated addition cases compared to their exact arithmetic counterparts. These findings imply that the approximation does not save computing costs for DLLM. This is contrary to how a human uses an approximation for easier computation [6]. However, the rounding case shows lower effective rank and lower JS divergence in the mid layers. We hypothesize the model reaches the answer faster due to the simplicity of the case.

Future work includes causal study of DLLM to isolate the arithmetic neurons [1], particularly approximation operations, extending the evaluation to larger benchmarks to gain statistical significance and providing mechanistic interpretability study tools to the community.

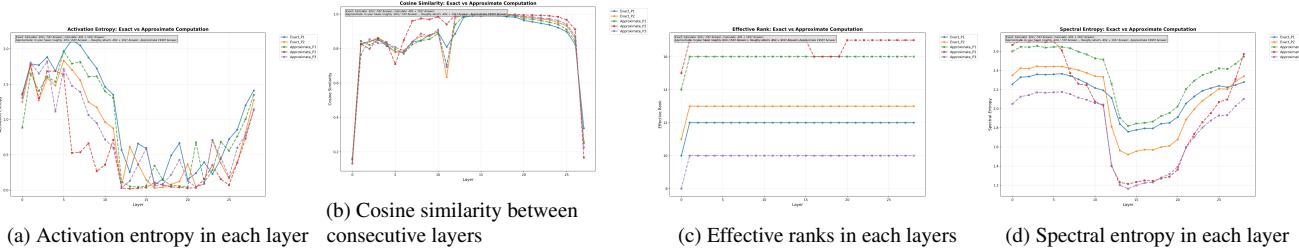


Figure 1: Cross layer comparisons

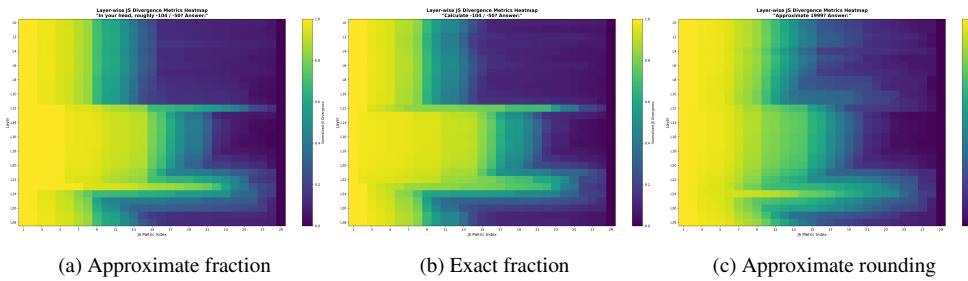


Figure 2: Heatmap of Jensen–Shannon divergence in each layer

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