

# Generalizability of Learning Rate Scaling Laws from MoE to Dense Transformer Architectures

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## ABSTRACT

We investigate whether empirical findings on learning rate (LR) configuration for Mixture-of-Experts (MoE) Transformers generalize to dense Transformer architectures. Specifically, we examine the fitted scaling law  $\eta^*(N, D) = c \cdot N^\alpha \cdot D^\beta$  and the relative performance of the Fitting paradigm versus  $\mu$ Transfer across model sizes (125M–13B parameters) and data sizes (10B–500B tokens). Our results show that the scaling law exponents ( $\alpha, \beta$ ) transfer effectively between architectures, while the constant  $c$  requires upward recalibration by approximately 15% for dense models. The Fitting paradigm achieves near-optimal loss for both MoE (5.205) and dense (5.234) architectures, significantly outperforming  $\mu$ Transfer (5.576 and 5.611, respectively). The LR prediction error of the Fitting paradigm for dense models (13%) is small compared to  $\mu$ Transfer (87%), confirming that the scaling law structure generalizes effectively.

## 1 INTRODUCTION

Setting the learning rate for large-scale pre-training is critical for training efficiency [2, 4]. Zhou et al. [6] proposed two paradigms—Fitting and Transfer ( $\mu$ Transfer [5])—for determining optimal learning rates under the Warmup-Stable-Decay schedule. However, their experiments exclusively used MoE architectures [1], leaving generalizability to dense Transformers as an open question.

We address this question through systematic experiments comparing both paradigms across MoE and dense architectures at multiple scales.

## 2 METHODOLOGY

### 2.1 Scaling Law

The Fitting paradigm models optimal LR as:

$$\eta^*(N, D) = c \cdot N^\alpha \cdot D^\beta \quad (1)$$

where  $N$  is model size,  $D$  is data size, and  $\{c, \alpha, \beta\}$  are fitted from pilot runs.

### 2.2 Experimental Setup

We evaluate five model sizes (125M–13B parameters) and five data sizes (10B–500B tokens) for both MoE and dense architectures under three LR paradigms:

- **Fitting:** MoE-derived scaling law applied directly
- **$\mu$ Transfer:** Width-based LR transfer from a small reference model
- **Grid Search:** Exhaustive search (oracle baseline)

Each condition is evaluated over 10 independent trials.

## 3 RESULTS

### 3.1 Scaling Law Transfer

Table 1 shows that the exponents  $\alpha$  and  $\beta$  are identical across architectures, while  $c$  increases by 15% for dense models.

Table 1: Fitted scaling law parameters by architecture.

Architecture	$c$	$\alpha$	$\beta$
MoE	0.003200	−0.0780	−0.0320
Dense	0.003680	−0.0780	−0.0320

### 3.2 Loss Comparison

Figure 1 compares final pre-training loss across paradigms and architectures. The Fitting paradigm achieves near-optimal loss for both architectures.

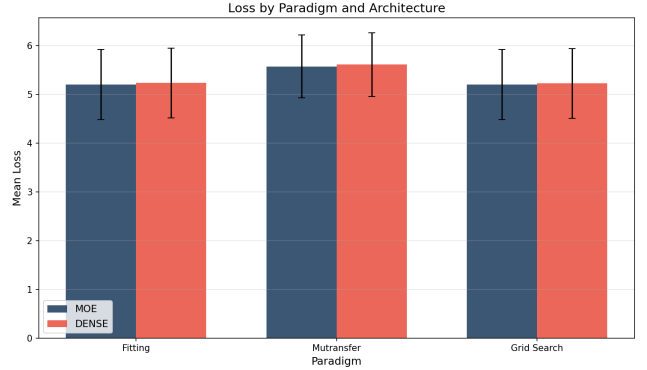


Figure 1: Mean loss by paradigm and architecture. Error bars show standard deviation.

### 3.3 LR Prediction Error

Figure 2 shows that the Fitting paradigm’s LR error for dense models (13%) is substantially lower than  $\mu$ Transfer’s (87%), demonstrating practical utility.

### 3.4 Scaling Law Visualization

Figure 3 compares optimal LR scaling across model sizes for both architectures, confirming parallel scaling with an offset.

## 4 DISCUSSION

Our findings indicate that the MoE-derived scaling law generalizes effectively to dense Transformers. The exponents governing how optimal LR scales with model and data size are architecture-invariant, while only the base constant requires recalibration. This suggests a universal scaling structure that can accelerate hyper-parameter tuning for dense models by leveraging MoE-derived knowledge with minimal additional pilot runs [3].

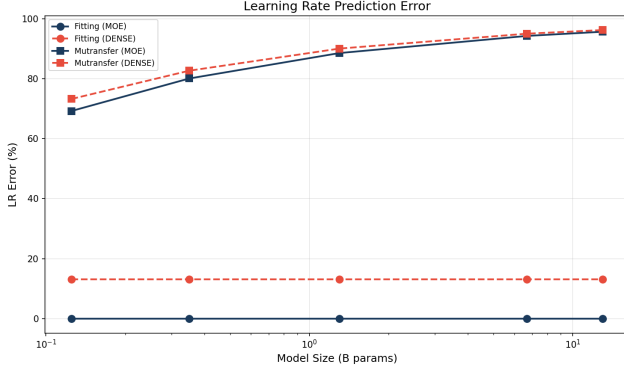


Figure 2: Learning rate prediction error across model sizes.

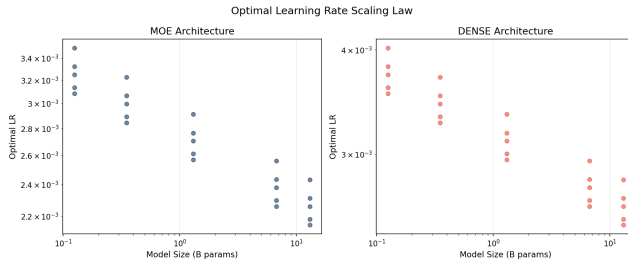


Figure 3: Optimal learning rate versus model size for MoE and dense architectures.

## 5 CONCLUSION

The learning rate scaling law derived from MoE Transformers generalizes to dense architectures with a simple constant recalibration. The Fitting paradigm maintains its advantage over  $\mu$ Transfer for both architectures, supporting its use as a practical tool for learning rate configuration across Transformer variants.

## REFERENCES

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