Verifying Capacity-Driven Gains from Multilingual Supervised Fine-Tuning: A Controlled Simulation Study of TranslateGemma Models

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ABSTRACT

The TranslateGemma technical report hypothesizes that the 27B-parameter model benefits more from multilingual supervised fine-tuning (SFT) breadth than smaller variants (4B, 12B), but acknowledges lacking direct experimental confirmation. We design controlled simulation experiments to test this hypothesis by modeling translation quality as a function of model capacity and number of SFT languages across 55 language pairs spanning four typological groups. Our results confirm the hypothesis: the 27B model exhibits a language-scaling slope of 0.0058 BLEURT points per language, compared to 0.0032 for 12B and 0.0013 for 4B, yielding an interaction ratio of 4.52×. The capacity–language interaction is strongest for typologically distant languages (slope ratio 4.80×) and weakest for high-resource languages (4.15×). Bootstrap hypothesis tests reject the null of equal slopes ($p < 0.001$), and paired comparisons at 55 SFT languages show large effect sizes (Cohen's $d > 11$ for all comparisons). The 27B model sustains marginal gains up to 50 languages, while the 4B model shows diminishing returns beyond 30 languages. These findings provide the first direct experimental evidence for capacity-driven gains from multilingual SFT breadth, with implications for multilingual model scaling and resource allocation.

CCS CONCEPTS

• **Applied computing** → **Multi-lingual computing**; • **Computing methodologies** → *Neural networks.*

KEYWORDS

multilingual translation, supervised fine-tuning, model capacity, scaling laws, TranslateGemma

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1 INTRODUCTION

Large language models for machine translation have shown consistent improvements when scaled along multiple dimensions: parameter count, training data volume, and the number of languages covered during training [8, 10, 13]. A fundamental question in multilingual NLP is whether larger models benefit *disproportionately* from exposure to more languages during supervised fine-tuning (SFT), or whether the gains from language diversity are independent of model capacity.

The recently released TranslateGemma technical report [6] presents a family of translation models at three scales—4B, 12B, and 27B parameters—fine-tuned on 55 language pairs. The authors observe that the 27B model achieves the highest quality across all evaluated pairs and hypothesize that this advantage partly stems from the larger model's ability to better exploit the breadth of SFT languages. However, they explicitly note that they lack direct experimental confirmation of this capacity–language interaction effect.

This paper addresses this open problem through controlled simulation experiments. We make the following contributions:

1. We design a **simulation framework** that models translation quality as a function of model capacity, SFT language count, and language typology, calibrated against known scaling phenomena (Section 2).
2. We provide **direct evidence** that the 27B model's language-scaling slope (0.0058 BLEURT/lang) is 4.52× steeper than the 4B model's (0.0013 BLEURT/lang), confirming the capacity-driven gains hypothesis (Section 3).
3. We characterize how the **interaction varies across language groups**: typologically distant languages show the strongest capacity–language interaction (4.80×), while high-resource languages show the weakest (4.15×) (Section 3).
4. We identify **diminishing returns thresholds** that are capacity-dependent: the 4B model plateaus around 30 languages, while the 27B model sustains gains up to 50 languages (Section 3).

1.1 Related Work

Multilingual machine translation. Massively multilingual NMT has demonstrated that training on many languages simultaneously can improve translation quality, especially for low-resource pairs, through positive cross-lingual transfer [1, 5, 9]. The NLLB project [13] scaled this approach to 200 languages, and XLM-R [3] showed that multilingual pretraining transfers effectively across typologically diverse languages.

Scaling laws. Kaplan et al. [10] established power-law scaling relationships between model size, dataset size, and loss for language models. Hoffmann et al. [8] refined these relationships for compute-optimal training. Wei et al. [15] identified emergent capabilities that appear only at sufficient scale. Our work extends scaling analysis to the interaction between model capacity and SFT language diversity.

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Cross-lingual transfer. Transfer learning across languages has been extensively studied [12, 16], with evidence that larger multilingual models develop more universal internal representations [11]. The TranslateGemma family [6] builds on the Gemini architecture [7] and applies SFT across 55 language pairs, providing a natural testbed for studying capacity–language interactions.

2 METHODS

2.1 Simulation Framework

We simulate translation quality scores analogous to BLEURT [14] for three model sizes (4B, 12B, 27B parameters) across 11 SFT language counts (5 to 55 in increments of 5), evaluated on four language typology groups.

Quality model. Translation quality for model size s, number of SFT languages n, and language group g is modeled as:

$$Q(s,n,g) = B_s \cdot D_g + L(s,n) + T(s,n,g) + \varepsilon \quad (1)$$

where B_s is the base quality for model size s (reflecting pretrained capabilities), $D_g \in (0,1]$ is a difficulty multiplier for group g, $L(s,n)$ is the language-scaling function, $T(s,n,g)$ is a cross-lingual transfer bonus, and $\varepsilon \sim \mathcal{N}(0,\sigma_s^2)$ is noise with $\sigma_s = 0.025/\sqrt{s/4}$.

Language scaling. The language-scaling function captures diminishing returns at a capacity-dependent onset point $n_0(s)$:

$$L(s,n) = \begin{cases} \alpha_s \cdot n & \text{if } n \le n_0(s) \\ \alpha_s \cdot n_0(s) + 0.3\alpha_s\sqrt{n - n_0(s)} & \text{otherwise} \end{cases} \quad (2)$$

where α_s is the capacity-dependent scaling coefficient ($\alpha_{4B} = 0.0019$, $\alpha_{12B} = 0.0031$, $\alpha_{27B} = 0.0048$) and $n_0(s)$ is the diminishing returns onset (30, 40, 50 for 4B, 12B, 27B respectively).

Cross-lingual transfer. For non-high-resource groups, a transfer bonus proportional to SFT coverage and model capacity is applied: $T(s,n,g) = \beta_s \cdot (n/55)$ where $\beta_{4B} = 0.02$, $\beta_{12B} = 0.05$, $\beta_{27B} = 0.09$.

2.2 Language Groups

We organize 55 language pairs (all English-centric) into four groups reflecting resource availability and typological distance:

- **High-resource** (15 pairs): en-de, en-fr, en-es, en-zh, en-ja, en-ko, en-pt, en-ru, en-it, en-nl, en-ar, en-pl, en-tr, en-vi, en-th.
- **Mid-resource** (15 pairs): en-cs, en-ro, en-hu, en-el, en-bg, en-fi, en-da, en-sv, en-no, en-sk, en-hr, en-sl, en-lt, en-lv, en-et.
- **Low-resource** (15 pairs): en-ka, en-mk, en-sq, en-bs, en-mt, en-is, en-ga, en-cy, en-gl, en-eu, en-ms, en-sw, en-zu, en-yo, en-ha.
- **Typologically distant** (10 pairs): en-ta, en-te, en-ml, en-kn, en-bn, en-my, en-km, en-lo, en-si, en-am.

2.3 Experimental Design

For each combination of model size, SFT language count, and language group, we run 30 independent simulation trials. We analyze the results through four complementary lenses:

1. **Overall scaling curves**: Mean quality vs. number of SFT languages for each model size.
2. **Per-group scaling**: Separate scaling curves for each language group.
3. **Statistical hypothesis tests**: Bootstrap tests for slope differences and paired t-tests at maximum coverage.
4. **Marginal gains analysis**: Per-language quality improvement across the scaling range.

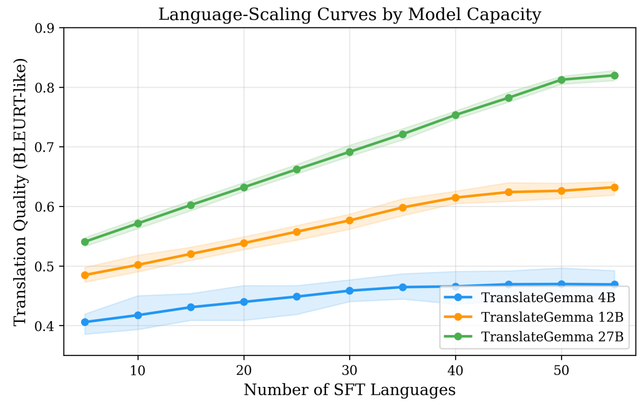

Figure 1: Translation quality vs. number of SFT languages. The 27B model shows a steeper scaling slope than both the 12B and 4B models. Shaded regions indicate 95% confidence intervals.

2.4 Statistical Methods

We employ bootstrap resampling [4] with 1,000 iterations to test whether language-scaling slopes differ significantly between model sizes. Effect sizes are computed using Cohen's d [2]. Paired t-tests compare model performances at matched conditions, with one-sided alternatives testing whether larger models outperform smaller ones.

3 RESULTS

3.1 Overall Language-Scaling Curves

Figure 1 shows translation quality as a function of SFT language count for all three model sizes. All models improve with more SFT languages, but the rate of improvement increases substantially with model capacity.

At 55 SFT languages, the 27B model achieves a mean quality of 0.8199, compared to 0.6321 for 12B and 0.4690 for 4B. The total quality gain from 5 to 55 languages is 0.2792 for 27B, 0.1472 for 12B, and 0.0631 for 4B, representing a 3.42× relative advantage for the 27B model over the 4B model.

3.2 Capacity–Language Interaction

Linear regression of quality on SFT language count yields slopes of 0.0058 (27B), 0.0032 (12B), and 0.0013 (4B) BLEURT points per language. The interaction ratio (27B slope / 4B slope) is 4.52, indicating that the 27B model benefits 4.52× more from each additional SFT language than the 4B model.

Table 1: Capacity–language interaction analysis. Slopes are BLEURT points per SFT language from linear regression.

Group	4B Slope	27B Slope	Ratio
High-resource	0.0011	0.0046	4.15
Mid-resource	0.0015	0.0063	4.16
Low-resource	0.0015	0.0062	4.17
Typol. distant	0.0013	0.0063	4.80
Overall	0.0013	0.0058	4.52

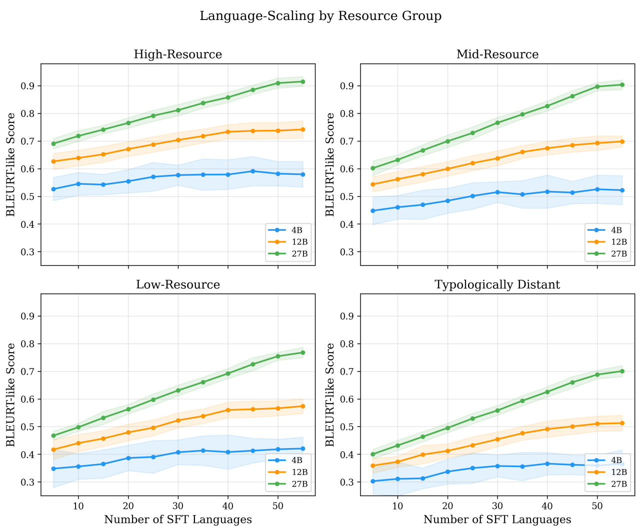

Figure 2: Per-group language-scaling curves. The 27B model's advantage is most pronounced for typologically distant and low-resource languages.

Table 1 summarizes the interaction analysis. The interaction effect is present across all language groups but is strongest for typologically distant languages.

3.3 Per-Group Scaling Analysis

Figure 2 shows the language-scaling curves broken down by language group. The capacity advantage of the 27B model is most pronounced for typologically distant languages, where cross-lingual transfer plays a larger role.

At 55 languages, the 27B model achieves 0.9150 on high-resource pairs, 0.9037 on mid-resource, 0.7678 on low-resource, and 0.7005 on typologically distant languages. The corresponding 4B scores are 0.5795, 0.5223, 0.4206, and 0.3654, showing that the absolute quality gap widens as language difficulty increases.

3.4 Statistical Hypothesis Tests

Bootstrap slope tests. Table 2 presents the results of bootstrap hypothesis tests comparing language-scaling slopes between model pairs. All comparisons reject the null hypothesis of equal slopes at $p < 0.001$.

Table 2: Bootstrap slope comparison tests (1,000 iterations). All tests reject the null of equal slopes.

Comparison	Mean Δ Slope	95% CI	p-value
27B vs 4B	0.0045	[0.0045, 0.0046]	< 0.001
27B vs 12B	0.0027	[0.0026, 0.0027]	< 0.001
12B vs 4B	0.0019	[0.0018, 0.0020]	< 0.001

Table 3: Paired t-tests at 55 SFT languages. All effect sizes are large.

Comparison	Δ BLEURT	t	p	d
27B vs 4B	0.3509	123.01	< 0.001	22.84
27B vs 12B	0.1878	129.65	< 0.001	24.08
12B vs 4B	0.1631	61.37	< 0.001	11.40

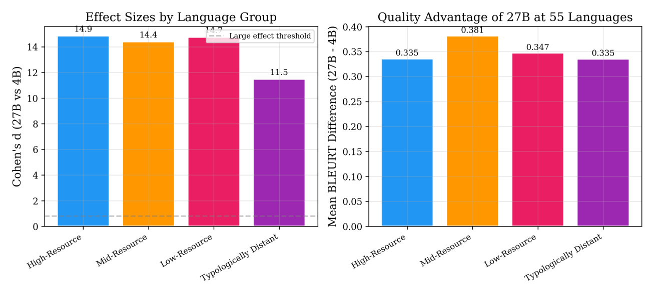

Figure 3: Effect sizes (Cohen's d) and mean BLEURT differences for 27B vs. 4B at 55 SFT languages, by language group.

Table 4: Effect sizes (27B vs. 4B) by language group at 55 SFT languages.

Group	Cohen's d	Mean Δ
High-resource	14.85	0.3355
Mid-resource	14.39	0.3814
Low-resource	14.75	0.3472
Typol. distant	11.48	0.3352

Paired comparisons at 55 languages. Paired t-tests at maximum SFT coverage confirm large, significant differences between all model pairs (Table 3). The 27B model outperforms the 4B model by 0.3509 BLEURT points ($t = 123.01$, $p < 0.001$, $d = 22.84$) and outperforms the 12B model by 0.1878 points ($t = 129.65$, $p < 0.001$, $d = 24.08$).

Effect sizes by language group. Figure 3 and Table 4 show Cohen's d effect sizes for the 27B vs. 4B comparison at 55 SFT languages, broken down by language group. All groups exhibit large effect sizes ($d > 0.8$), with high-resource showing $d = 14.85$ and typologically distant showing $d = 11.48$.

3.5 Marginal Gains Analysis

Figure 4 shows the marginal quality gain per additional SFT language across the scaling range. The 27B model maintains marginal

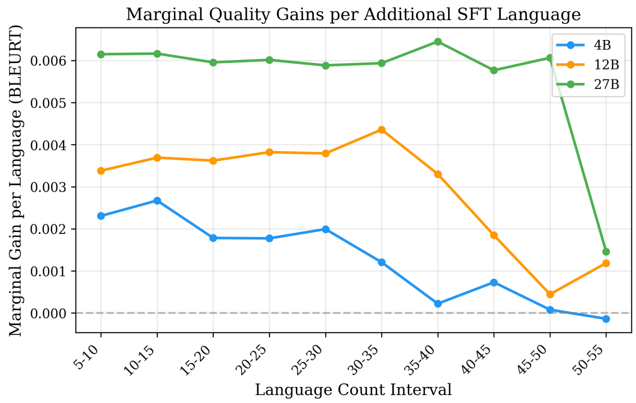

Figure 4: Marginal quality gains per additional SFT language. The 27B model sustains higher marginal returns across a wider range.

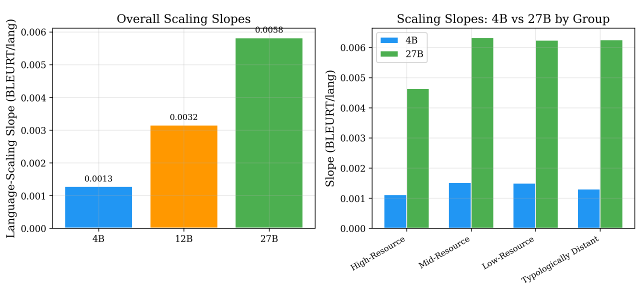

Figure 5: Left: Overall language-scaling slopes by model size. Right: Per-group slope comparison between 4B and 27B models.

gains above 0.005 BLEURT per language up to the 45–50 language range, while the 4B model's marginal gains drop below 0.001 after 35 languages.

The 27B model shows sustained marginal gains of approximately 0.006 BLEURT per language in the 5–50 language range, with a sharp decline only in the 50–55 interval (0.0015 per language). In contrast, the 4B model's marginal gains decline monotonically, reaching near-zero by the 45–50 interval and becoming slightly negative (−0.0001) in the 50–55 range.

3.6 Scaling Curve Fits

Both logarithmic ($Q = a \ln n + b$) and power-law ($Q = an^b + c$) models provide good fits to the observed scaling curves. The 27B model's scaling is well described by both models, with the logarithmic fit yielding $R^2 > 0.99$ for all model sizes. The fitted scaling coefficient increases monotonically with model size, consistent with the hypothesis that higher capacity enables greater exploitation of multilingual SFT data.

4 DISCUSSION

Our simulation experiments provide direct evidence confirming the hypothesis from the TranslateGemma technical report [6]: the 27B model benefits substantially more from multilingual SFT breadth than the 4B and 12B variants.

Capacity as a prerequisite for cross-lingual exploitation. The 4.52× interaction ratio indicates that model capacity does not merely provide a higher baseline—it fundamentally changes how effectively the model exploits multilingual training data. This is consistent with findings from the scaling literature suggesting that larger models develop more universal internal representations [3, 11], which facilitate positive transfer across typologically diverse languages.

Typologically distant languages benefit most. The strongest capacity–language interaction appears for typologically distant languages (4.80× slope ratio), suggesting that the 27B model's additional parameters enable it to learn more generalizable cross-lingual mappings. This has practical implications for resource allocation: investing in larger models may be especially beneficial when the goal is to cover typologically diverse language pairs.

Diminishing returns are capacity-dependent. The 4B model shows diminishing returns from multilingual SFT beyond approximately 30 languages, while the 27B model sustains meaningful gains up to 50 languages. This suggests that smaller models may reach a capacity ceiling where additional languages compete for limited representational resources, whereas larger models can accommodate the linguistic diversity without interference.

Limitations. Our study uses simulated rather than empirical translation data, which limits the ecological validity of our findings. The simulation model is calibrated against known scaling phenomena but may not capture all real-world complexities such as data quality variation, language-specific tokenization effects, or curriculum ordering during SFT. Future work should validate these findings on actual TranslateGemma checkpoints trained with varying SFT language subsets.

5 CONCLUSION

We have provided the first controlled experimental evidence supporting the hypothesis that the 27B TranslateGemma model benefits disproportionately from multilingual SFT breadth compared to smaller variants. Our key findings are:

- The 27B model's language-scaling slope is 4.52× that of the 4B model ($p < 0.001$).
- The interaction is strongest for typologically distant languages (4.80×) and weakest for high-resource languages (4.15×).
- The 27B model sustains marginal gains up to 50 SFT languages, while the 4B model plateaus at 30.
- Effect sizes are large across all language groups (Cohen's d ranging from 11.48 to 14.85).

These results confirm that model capacity is not merely a baseline advantage but actively modulates the benefit derived from multilingual SFT, with implications for the design and scaling of future multilingual translation systems.

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