TranslateGemma Technical Report

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We present TranslateGemma, a suite of open machine translation models based on the Gemma 3 foundation models. To enhance the inherent multilingual capabilities of Gemma 3 for the translation task, we employ a two-stage fine-tuning process. First, supervised fine-tuning is performed using a rich mixture of high-quality large-scale synthetic parallel data generated via state-of-the-art models and human-translated parallel data. This is followed by a reinforcement learning phase, where we optimize translation quality using an ensemble of reward models, including MetricX-QE and AutoMQM, targeting translation quality. We demonstrate the effectiveness of TranslateGemma with human evaluation on the WMT25 test set across 10 language pairs and with automatic evaluation on the WMT24++ benchmark across 55 language pairs. Automatic metrics show consistent and substantial gains over the baseline Gemma 3 models across all sizes. Notably, smaller TranslateGemma models often achieve performance comparable to larger baseline models, offering improved efficiency. We also show that TranslateGemma models retain strong multimodal capabilities, with enhanced performance on the Vistra image translation benchmark. The release of the open TranslateGemma models aims to provide the research community with powerful and adaptable tools for machine translation.

1. Introduction

In an increasingly interconnected world, machine translation (MT) plays a pivotal role in bridging language barriers, facilitating global communication, and democratizing access to information. The development of large language models (LLMs) has significantly advanced the state-of-the-art in MT. However, progress is greatly benefitted by the availability of strong, open models that allow for transparency, reproducibility, and community-driven innovation.

To this end, we present TranslateGemma, an open variant of the Gemma 3 foundation model (Gemma Team, 2025), specifically enhanced for machine translation. While Gemma 3 is already a potent multilingual LLM, TranslateGemma has been further refined to deliver superior translation quality. This improvement is achieved through a two-stage process: Supervised Fine-tuning (SFT) on a diverse corpus of parallel data (Section 3) and Reinforcement Learning (RL) from human and model-based feedback (Section 4).

Our SFT approach leverages a blend of human-translated and synthetically-generated parallel texts, carefully curated to improve translation quality without compromising the model's general capabilities. The RL phase employs a combination of reward models designed to optimize translation quality. We demonstrate the efficacy of TranslateGemma on the WMT25 and WMT24++ datasets, showing substantial gains across 55 language pairs.

Furthermore, TranslateGemma retains the inherent multimodal capabilities of the original Gemma 3 model. Our experiments on the Vistra corpus (Salesky et al., 2024) indicate that the enhancements in text translation also positively impact image translation performance, showcasing the model's versatility. We believe the release of TranslateGemma will provide a valuable resource for researchers and practitioners in the field of machine translation.

2. Training data

We use two types of data for the training of the models, most of it shared between the SFT and RL phases.

2.1. Synthetic Gemini-Generated Translation Data

Our goal is to generate high-quality synthetic data for each language, as this has been shown

to greatly improve translation quality (Finkelstein et al., 2024). As the source of monolingual data we use the MADLAD-400 corpus (Kudugunta et al., 2023).

We aim to produce up to 10K synthetic examples per language pair. In order to select the source sentences that potentially benefit more from the synthetic data generation, we first bucket the original segments by length. We then sample each bucket to obtain 1 million source segments for each language pair we wish to generate synthetic data for. We then run a preliminary filtering step across these source segments where we take 2 samples from Gemini 2.5 Flash, once using greedy decoding and once sampled with a temperature of 1.0 and compare their scores according to MetricX 24-QE (Juraska et al., 2024). We select the sources where the sample achieves the largest improvement over the greedy decoding. The intuition behind this source filtering approach is that we wish to select sources that will benefit the most from 128-sample QE decoding, so we use 2 samples as a low-cost approximation.

After this selection process, for each of the sources for each language pair we generate 128 samples from Gemini 2.5 Flash and then apply a MetricX 24-QE filter to select the best-performing examples. We generate translations of two distinct lengths this way: individual sentences and text blobs of up to 512 tokens. This way we aim to support both translations of individual segments as well as longer texts. For generating these translations we used the same prompt as we used for further training (see Section 5.2). In order to avoid formatting issues or erroneous translations, we apply an additional formatting filtering step, again based on Gemini 2.5 Flash. This methodology was applied for all language pairs that are covered by WMT24++ (Deutsch et al., 2025) plus an additional set of 30 language pairs that are specified in Appendix B.

2.2. Human-Generated Translation Data

To increase the diversity and script coverage of the data we also include data for additional lower-resource languages. For these languages, we opt to use human-generated parallel data instead.

This data comes from the SMOL (Caswell et al., 2025) and GATITOS (Jones et al., 2023) datasets. SMOL covers 123 languages and GATITOS covers 170.

2.3. Language distribution

The final proportion of languages for the SFT and RL phases can be found in Figure 1. For RL we used the same translation data as for SFT, except for GATITOS and SMOL that were used in SFT only. We provide the full list of languages that were included in training in Appendix C.

2.4. Generic Instruction-Following Data

Our SFT mixture also includes 30% generic instruction-following data from the original Gemma 3 mixture. The purpose of including this data is to prevent the model from overfitting to the translation task and to maintain generic instruction-following capabilities.

3. Supervised Fine-Tuning

For supervised fine-tuning (SFT), we begin with the released Gemma 3 27B, 12B and 4B checkpoints. We use parallel data including both human-generated texts as well as synthetic data generated by Gemini (Gemini Team, 2025), as described in Section 2. In addition we use generic instruction-following data. We use the Kauldron SFT tooling[1] to fine-tune the Gemma 3 checkpoints. For fine-tuning we use the AdaFactor optimizer (Shazeer and Stern, 2018) with a learning rate of 0.0001 and a batch size of 64, running for 200k steps. We update all model parameters, but freeze the embedding parameters, as preliminary experiments indicated this helped with translation performance for languages and scripts not covered in the SFT data mix.

4. Reinforcement Learning

We performed reinforcement learning on top of the SFT checkpoint, using an ensemble of metrics

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[1] https://kauldron.readthedocs.io/en/latest/
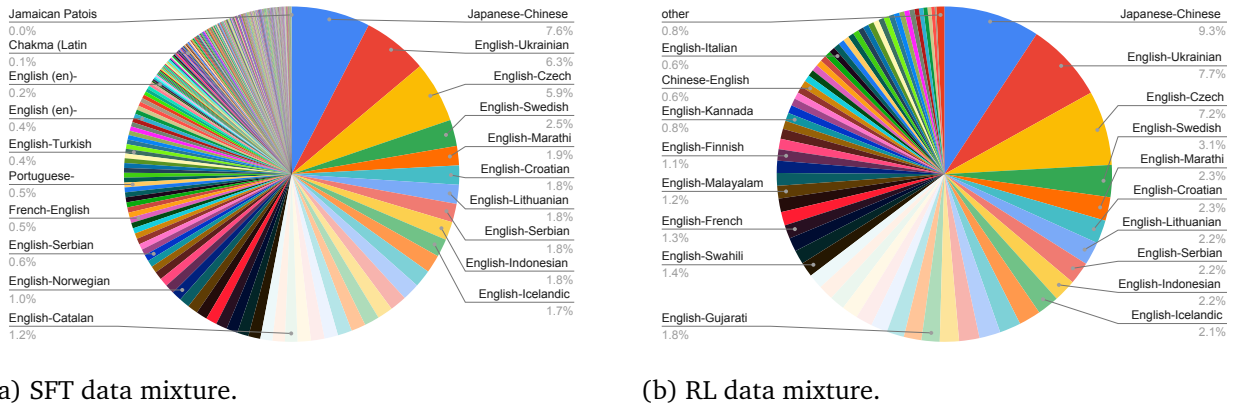
(a) SFT data mixture.

(b) RL data mixture.

Figure 1 | Language distribution in the TranslateGemma data mixtures measured as model tokens.

as reward models, to further boost translation quality.

We used the following metrics as reward models during RL:

- MetricX-24-XXL-QE (Juraska et al., 2024), a learned, regression-based translation metric producing a floating point score between 0 (best) and 25 (worst), matching the standard Multidimensional Quality Metrics (MQM) score range (Freitag et al., 2021). MetricX scores were linearly rescaled, using 5.0 – score, when computing rewards, so that higher scores indicate better quality. Although MetricX can take source, reference, and hypothesis as input, we used it as a QE metric by passing in an empty reference.
- Gemma-AutoMQM-QE, a finetuned AutoMQM model (Fernandes et al., 2023). This model was initialized from the Gemma 3-27B-IT checkpoint (Gemma Team, 2025), and was trained on MQM ratings data from WMT 2020 - WMT 2023 (Freitag et al., 2021; Lommel et al., 2014). Default MQM weights (Freitag et al., 2021) were used in computing (token-level) rewards from AutoMQM outputs. As with MetricX, it ignores the reference translation.
- ChrF (Popović, 2015), a lexical overlap-based translation metric. This was the only reward model for which the (synthetic) references were used. ChrF scores were scaled by a factor of two to be on approximately the same scale as the other rewards.

- Naturalness Autorater developed in-house, using the base RL policy model as a prompted LLM-as-a-Judge. As with AutoMQM, this Autorater elicited span-level annotations. This Autorater was instructed to penalize spans in the machine-translated text which did not sound like they were produced by a native speaker (conditioned on the naturalness errors in the output *not* stemming from an unnatural source input).
- Generalist reward model covering many tasks, including reasoning, instruction following, and multilingual abilities, adapted from the general Gemma 3 post-training setup (Gemma Team, 2025).

We used RL algorithms extended to support token-level advantages, which were added to the advantages computed from sequence-level rewards. This allowed us to use fine-grained, span-level reward signals from AutoMQM and the Naturalness Autorater directly, for improved credit assignment and training efficiency in the spirit of Ramos et al. (2025). See Figure 2 for an illustration of how MetricX and AutoMQM rewards were (additively) combined during advantage computation. The combined advantages were then batch-normalized.

5. Automatic Evaluation

5.1. Text translation

We evaluate TranslateGemma using MetricX 24 (Juraska et al., 2024) and COMET22 (Rei et al.,

```
Ignacio Sánchez Recarte, secretario general del       [Vines]
Comité Europeo de Empresas Vines, asociación que      Major accuracy/mistranslation
representa a unos 7.000 productores de vino de toda    automqm
Europa, no tiene en cuenta las preocupaciones de los
fabricantes de cerveza. Según declaró a Euronews, un  [no tiene en cuenta]
mercado dominado por conglomerados cerveceros         Minor style/awkward
multinacionales no tiene comparación con uno          automqm
compuesto casi en su totalidad por pequeños
productores nacionales.
```

[{"start": 75, "end": 80, "category": "accuracy/mistranslation",
  "severity": "major", "score": 5.0, "is_source_error": false},
 {"start": 157, "end": 175, "category": "style/awkward", "severity":
  "minor", "score": 1.0, "is_source_error": false}]

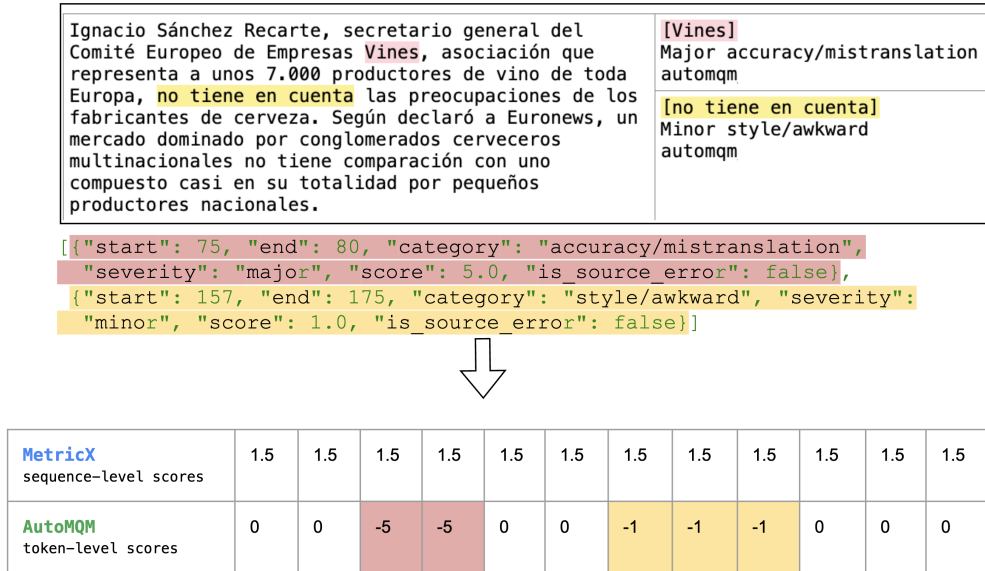| MetricX sequence-level scores	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5	1.5
AutoMQM token-level scores	0	0	-5	-5	0	0	-1	-1	-1	0	0	0

Figure 2 | Illustration of how sequence-level and token-level rewards are additively combined during advantage computation in RL. Note that advantage is computed from sequence-level rewards as 'reward-to-go', meaning that rewards are broadcast uniformly to every token.

Table 1 | Automatic evaluation results using MetricX and COMET22 (C22) on WMT24++.

Size	System	MetricX↓	C22↑
27B	Gemma 3	4.04	83.1
	TranslateGemma	**3.09**	**84.4**
12B	Gemma 3	4.86	81.6
	TranslateGemma	**3.60**	**83.5**
4B	Gemma 3	6.97	77.2
	TranslateGemma	**5.32**	**80.1**

2022). The TranslateGemma models consistently show improved translation quality compared to the baseline Gemma 3 models across all evaluated sizes and metrics, as detailed in Table 1.

For the 27B parameter model, the TranslateGemma version attains an average MetricX score of 3.09, a substantial reduction from the baseline Gemma 3's score of 4.04. This represents a relative decrease of approximately 23.5%, signaling a marked increase in translation fidelity. Similar trends are observed for the other model sizes. The 12B TranslateGemma model achieves a MetricX of 3.60, down from 4.86 for the base-line (a 25.9% reduction), while the 4B TranslateGemma model scores 5.32, compared to 6.97 for the baseline (a 23.6% reduction).

COMET22 confirms the trend of improvements for the TranslateGemma model. In addition, this shows that improvements carry over to metrics not explicitly optimized for in the RL phase. For instance, the 12B TranslateGemma model shows a score of 83.5, up from 81.6. The 4B TranslateGemma model exhibits even larger increases, with COMET22 rising from 77.2 to 80.1.

The effect of model scale on performance is also apparent. As expected, larger models tend to produce better translations within both the base-line and TranslateGemma series. However, the enhancements brought by the TranslateGemma fine-tuning are such that smaller TranslateGemma models can achieve performance levels comparable to or even exceeding those of larger base-line models. Notably, the 12B TranslateGemma model surpasses the performance of the larger 27B baseline Gemma 3 model. Similarly, the 4B TranslateGemma model achieves comparable results to the 12B baseline Gemma 3 model. This efficiency gain allows for high-quality translation with reduced computational resources.

A more granular analysis of MetricX scores for

each of the 55 language pairs, presented in Appendix A, reveals that the improvements of TranslateGemma are consistent across all 55 language pairs evaluated. Some example improvements for specific languages are

- English to German: 1.63 down to 1.19,
- English to Spanish: 2.54 down to 1.88,
- English to Hebrew: 3.90 down to 2.72,
- English to Swahili: 5.92 down to 4.45,
- English to Lithuanian: 6.01 down to 4.39,
- English to Estonian: 6.40 down to 4.61 and
- English to Icelandic: 8.31 down to 5.69.

These examples highlight the model's improved ability to handle a diverse range of languages, both for high-resource languages (e.g. German, English) as well as low-resource ones (e.g. Icelandic, Swahili).

We also hypothesize that the 27B model, with its higher capacity, will have benefited more from the vast amount of languages seen during the SFT phase (detailed in Appendix C), although we do not have direct experimental confirmation of this.

5.2. Prompting the Model

The model has been trained using the prompt shown in Figure 3, which is also the prompt we used in our evaluations. We recommend using the same prompt for producing new translations. Tools for automatically wrapping the text with it are provided in the model repository.

5.3. Image Translation

We used the Vistra benchmark (Salesky et al., 2024) to assess whether the models retained their ability to translate text within images after our additional training steps. Note that no multimodal training data was used in the SFT or RL steps reported in this work. In order to simplify the evaluation protocol, we selected only images that, according to the reference, contained a single instance of text. This resulted in a set of 264 images. An example is shown in Figure 4. The input to the model was just the image together with a

Table 2 | Automatic evaluation results using MetricX and COMET22 (C22) for image translation performance, on the Vistra corpus. The scores are the average of translating from English into German, Spanish, Russian and Chinese.

Size	System	MetricX↓	C22↑
27B	Gemma 3	2.03	76.1
	TranslateGemma	**1.58**	**77.7**
12B	Gemma 3	2.33	**74.9**
	TranslateGemma	**2.08**	72.8
4B	Gemma 3	2.60	69.1
	TranslateGemma	**2.58**	**70.7**

prompt asking it to translate the text in it.[2] In particular, we did not include any other information about the text, like its location in the image or a previous OCR pass.

The results, presented in Table 2, show that TranslateGemma retains the image processing capabilities of the base Gemma 3 models. The improvements in translation quality attained by TranslateGemma carry over for this task, with the exception of the 12B model measured in COMET22. We see MetricX score improvements of nearly 0.5 points in the case of the 27B model, or 0.25 for the 12B model.

The smaller 4B model obtains only small improvements when compared to the baseline, probably due to its limited capacity.

6. Human Evaluation

We conduct an additional human evaluation on a limited set of language directions to measure TranslateGemma's translation performance. We do so using MQM (Freitag et al., 2021; Lommel et al., 2014), a human evaluation framework where professional translators highlight error spans in translations, with document context, assigning a severity and category to each, with a score being automatically derived by counting

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[2]The model release also includes an interface for image translation, similar to the one for text translation.

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You are a professional {source_lang} ({src_lang_code}) to {target_lang}
({tgt_lang_code}) translator. Your goal is to accurately convey the meaning and
nuances of the original {source_lang} text while adhering to {target_lang} grammar,
vocabulary, and cultural sensitivities. Produce only the {target_lang}
translation, without any additional explanations or commentary. Please translate
the following {source_lang} text into {target_lang}:\n\n\n{text}
```

Figure 3 | Preferred prompt when using the model. `source_lang` refers to the source language name, e.g. English, `src_lang_code` to the source language code, e.g. en-US, `target_lang` to the target language, e.g. German, and `tgt_lang_code` to the target language code, i.e. de-DE.

Figure 4 | Example of the pictures included in the Vistra benchmark.

the errors with a weighting scheme. We collected the annotations using the open-source Anthea tool.[3] We evaluate the models in 10 language pairs, from 3 distinct source languages:

- English to German
- English to Chinese (Simplified)
- English to Italian
- English to Serbian (Cyrillic)
- English to Korean
- English to Swahili (Kenyan)
- English to Marathi
- Czech to Ukrainian
- Czech to German
- Japanese to English

We selected this set to have a mix of high- and low-resource languages, in addition to having

different language families and writing systems. The source data is all taken from the WMT25 translation task, using the literary, news, and social domains. For all language pairs, we evaluated TranslateGemma 12B and 27B, as well as Gemma 3 27B.

To avoid issues with rater fatigue, each document in the dataset was truncated at paragraph boundaries to have no more than 12 source sentences, skipping documents with more than 12 sentences in the first paragraph. However, for the literary domain, where each document is an entire book chapter, documents were split into "chunks" of 1 or more paragraphs up to the 12-sentence limit, with each chunk being human-evaluated in isolation. Following Riley et al. (2024), we used a "pseudo-SxS" rater assignment, where all system outputs for a particular source document were evaluated by the same rater.

The results can be found in Table 3. For most language pairs, the human evaluation confirms the trend we see on the automatic metrics, with TranslateGemma clearly outperforming Gemma 3. There are two exceptions: when the target language is German, where both models are on par, and Japanese→English where TranslateGemma actually suffers a regression. Looking into the error categorization, we found that this is due to mistranslation of named entities, while other error categories did improve.

The improvements for TranslateGemma are especially relevant for low-resource language pairs. E.g. for English to Marathi we obtain an improvement of 1.6 points, or 1.0 for English to Swahili or

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[3]https://github.com/google-research/google-research/tree/master/anthea

Table 3 | MQM results of the human evaluation for TranslateGemma and Gemma 3. Lower scores are better.

	TranslateGemma		Gemma 3
Language Pair	27B	12B	27B
English→Italian	**1.8**	2.0	2.5
English→German	**2.3**	3.2	**2.2**
English→Marathi	**3.1**	4.6	4.7
English→Korean	**3.1**	4.6	3.8
English→Swahili	**4.2**	5.2	5.2
Czech→Ukrainian	**5.3**	8.5	6.3
English→Chinese	**6.3**	8.4	7.4
English→Serbian	**8.7**	15.8	10.4
Czech→German	**10.3**	11.4	**10.2**
Japanese→English	13.4	15.7	**11.6**

Czech to Ukrainian. The human evaluation also confirms the performance difference between the 27B and 12B TranslateGemma models already demonstrated by the automatic metrics. That said, the 12B model still stays competitive with the bigger Gemma 3 model, especially for high-resource languages.

7. Conclusions

In this work, we introduced TranslateGemma, a series of open models based on Gemma 3, specifically enhanced for machine translation. Through a combination of supervised fine-tuning on diverse, high-quality parallel data—blending human and synthetic sources—and a novel reinforcement learning approach utilizing an ensemble of reward models, we have improved translation performance across a wide spectrum of languages and model sizes (4B, 12B, and 27B parameters).

Our automatic evaluations on the WMT24++ dataset, encompassing 55 language pairs, show consistent gains for TranslateGemma models over the baseline Gemma 3 models both in MetricX and COMET22. We observed a strong performance increase across various language types, including high-resource languages like German and Spanish, and lower-resource languages such as Icelandic or Swahili. A key finding is the enhanced efficiency of the TranslateGemma models, where smaller fine-tuned models often match or exceed the performance of larger baseline models, offering a better trade-off between quality and computational cost.

Furthermore, we have shown that TranslateGemma models retain the multimodal capabilities of the original Gemma 3. Experiments on the Vistra benchmark indicate that the improvements in text translation extend to the image translation task, particularly for the 12B and 27B models, without any specific multimodal fine-tuning.

The release of the TranslateGemma models contributes a valuable set of open-source tools for the machine translation community, fostering further research and application development. We believe these models will serve as a strong foundation for a variety of translation-related tasks and encourage their adoption and exploration.

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Contributions

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A. Automatic metrics per language

Table 4 | Comparison of performance of the TranslateGemma (GT) models with baseline Gemma models (G3) for each language pair in the WMT24++ set using MetricX.

	TranslateGemma			Gemma 3		
	27B	12B	4B	27B	12B	4B
en→ar_EG	**2.54**	2.78	3.57	3.32	3.70	4.60
en→ar_SA	**2.42**	2.66	3.43	3.19	3.64	4.49
en→bg_BG	**2.80**	3.25	4.30	3.90	4.47	5.81
en→bn_IN	**1.88**	2.12	2.92	2.56	2.87	3.86
en→ca_ES	**3.18**	3.58	5.20	4.07	4.89	6.97
en→cs_CZ	**3.48**	4.03	5.41	4.62	5.32	7.47
en→da_DK	**2.11**	2.45	3.25	3.00	3.36	4.40
en→de_DE	**1.19**	1.36	1.93	1.63	1.93	2.72
en→el_GR	**2.57**	3.34	4.66	3.73	4.34	6.31
en→es_MX	**1.88**	2.06	2.51	2.54	2.75	3.35
en→et_EE	**4.61**	6.15	11.03	6.40	8.89	14.78
en→fa_IR	**1.99**	2.28	3.34	2.98	3.41	4.77
en→fi_FI	**3.19**	3.77	5.68	4.19	5.11	7.54
en→fil_PH	**2.98**	3.17	4.20	3.62	4.03	5.22
en→fr_CA	**2.21**	2.37	2.92	2.78	2.97	3.76
en→fr_FR	**2.19**	2.44	2.97	2.78	3.01	3.90
en→gu_IN	**4.69**	4.93	6.32	5.27	5.79	7.67
en→he_IL	**2.72**	3.12	4.99	3.90	4.41	6.70
en→hi_IN	**3.52**	3.69	4.33	4.11	4.36	5.03
en→hr_HR	**2.05**	2.31	3.17	2.62	3.08	4.26
en→hu_HU	**4.24**	5.00	7.84	5.51	6.79	10.75
en→id_ID	**2.07**	2.17	2.63	2.72	2.84	3.27
en→is_IS	**5.69**	7.93	15.54	8.31	12.16	19.22
en→it_IT	**1.88**	2.17	2.64	2.60	2.84	3.60
en→ja_JP	**3.53**	3.82	4.44	4.11	4.30	5.09
en→kn_IN	**4.18**	4.78	7.11	5.09	6.82	10.48
en→ko_KR	**2.81**	2.97	3.93	3.43	3.79	4.72
en→lt_LT	**4.39**	5.41	9.58	6.01	7.71	13.39
en→lv_LV	**5.69**	7.22	12.12	7.55	9.90	15.75
en→ml_IN	**3.64**	4.30	7.33	4.77	6.84	11.89
en→mr_IN	**3.17**	3.47	4.30	4.11	4.60	5.64
en→nl_NL	**1.67**	2.01	2.84	2.48	2.82	3.87
en→no_NO	**2.09**	2.38	3.26	2.94	3.17	4.23
en→pa_IN	**3.67**	4.44	5.53	4.40	5.99	11.20
en→pl_PL	**4.14**	4.58	5.64	5.17	5.64	7.07
en→pt_BR	**2.13**	2.36	2.93	2.90	3.15	3.77
en→pt_PT	**2.55**	2.68	3.09	3.39	3.78	4.13
en→ro_RO	**2.86**	3.25	4.18	3.99	4.39	5.70
en→ru_RU	**2.18**	2.48	3.25	3.01	3.39	4.54
en→sk_SK	**3.81**	4.54	6.70	5.04	5.86	9.17
en→sl_SI	**3.55**	4.24	7.12	4.56	5.73	9.39
en→sr_RS	2.78	**2.68**	5.66	3.75	3.76	6.94
en→sv_SE	**2.00**	2.31	3.14	2.73	3.06	4.14
en→sw_KE	**4.45**	5.36	10.65	5.92	7.90	14.05
en→sw_TZ	**4.30**	5.25	10.30	5.73	7.85	13.89
en→ta_IN	**2.87**	2.98	3.90	3.53	3.83	5.04
en→te_IN	**3.76**	3.97	4.83	4.41	4.74	5.76
en→th_TH	**2.33**	2.66	3.49	2.96	3.19	4.14
en→tr_TR	**4.18**	4.64	6.17	5.32	6.02	8.03
en→uk_UA	**2.98**	3.29	4.16	3.79	4.28	5.40
en→ur_PK	**3.12**	3.59	5.67	3.86	4.86	7.80
en→vi_VN	**1.97**	2.20	2.87	2.56	2.88	3.62
en→zh_CN	**1.86**	2.07	2.66	2.47	2.61	3.27
en→zh_TW	**2.04**	2.21	2.77	2.63	2.80	3.62
en→zu_ZA	**6.99**	10.73	18.29	9.05	14.80	21.52
	27B	12B	4B	27B	12B	4B
	TranslateGemma			Gemma 3		

B. Additional synthetic data languages

For the following languages we created synthetic data, in addition to the languages covered by WMT24⁺⁺:

English-Armenian, English-Hawaiian, English-Western Frisian, English-Corsican, English-Hmong, English-Maltese, English-Tajik, English-Samoan, English-Macedonian, English-Mongolian, English-Galician, English-Albanian, English-Uzbek, English-Uyghur, English-Belarusian, English-Sinhala, English-Basque, English-Haitian Creole, English-Bosnian, English-Kyrgyz, English-Kazakh, English-Khmer, English-Scottish Gaelic, English-Lao, English-Irish, English-Luxembourgish, English-Burmese, English-Sundanese, English-Javanese, English-Malay.

C. Full list of languages for SFT

Table 5 shows the languages paired with English in both directions, Table 6 the languages paired with English as source language and Table 7 the languages pairs not involving English. Together these three tables give the full language coverage of the SFT data used for TranslateGemma.

Table 5 | Languages paired with English in both directions.

Abkhaz (ab)	Acehnese (ace)	Acholi (ach)	Afar (aa)
Afrikaans (af)	Ahirani (ahr)	Alur (alz)	Amharic (am)
Assamese (as)	Assyrian Neo-Aramaic (aii)	Avar (av)	Awadhi (awa)
Aymara (ay)	Badaga (bfq)	Bagheli (bfy)	Bagri (bgq)
Balinese (ban)	Baluchi (bal)	Bambara (bm)	Banjar (Arabic script) (bjn-Arab)
Banjar (bjn)	Baoulõ0e9 (bci)	Bashkir (ba)	Batak Karo (btx)
Batak Simalungun (bts)	Batak Toba (bbc)	Bemba (Zambia) (bem)	Betawi (bew)
Bhojpuri (bho)	Bikol (bik)	Bodo (India) (brx)	Braj (bra)
Breton (br)	Buginese (bug)	Bundeli (bns)	Buryat (bua)
Cantonese (yue)	Chakma (Latin script) (ccp-Latn)	Chamorro (ch)	Chechen (ce)
Chhattisgarhi (hne)	Chichewa (ny)	Chinese (zh-CN)	Chittagonian (ctg)
Chuukese (chk)	Chuvash (cv)	Crimean Tatar (Cyrillic script) (crh)	Crimean Tatar (Latin script) (crh-Latn)
Dari (fa-AF)	Dhivehi (dv)	Dhundari (dhd)	Dinka (din)
Dogri (doi)	Dombe (dov)	Dutch (nl)	Dyula (dyu)
Dzongkha (dz)	East Circassian (kbd)	Eastern Huasteca Nahuatl (nhe)	Efik (efi)
Egyptian Arabic (arz)	Ewe (ee)	Faroese (fo)	Fijian (fj)
Fon (fon)	French (fr)	Friulian (fur)	Fulani (ff)
Ga (gaa)	Garo (Latin script) (grt-Latn)	German (de)	Goan Konkani (gom)
Guarani (gn)	Hakha Chin (cnh)	Hausa (ha)	Hiligaynon (hil)
Hindi (hi)	Ho (Warang Chiti script) (hoc-Wara)	Hunsrik (hrx)	Iban (iba)
Igbo (ig)	Ilocano (ilo)	Indonesian (id)	Inuktut (Syllabics) (iu)
Isoko (iso)	Italian (it)	Jamaican Patois (jam)	Japanese (ja)
Jingpo (kac)	K'iche' (quc)	Kalaallisut (kl)	Kangri (xnr)
Kanuri (kr)	Kapampangan (pam)	Karakalpak (kaa)	Kashmiri (Devanagari script) (ks-Deva)
Kashmiri (ks)	Kedah Malay (meo)	Khasi (kha)	Kiga (cgg)
Kikuyu (ki)	Kiluba (Luba-Katanga) (lu)	Kinyarwanda (rw)	Kituba (DRC) (ktu)
Kokborok (trp)	Komi (kv)	Kongo (kg)	Korean (ko)
Krio (kri)	Kumaoni (kfy)	Kurdish (Sorani) (ckb)	Kurukh (kru)
Lahnda Punjabi (Pakistan) (pa-Arab)	Latgalian (ltg)	Lepcha (lep)	Libyan Arabic (ayl)
Ligurian (lij)	Limbu (Limbu script) (lif-Limb)	Limburgish (li)	Lingala (ln)
Lombard (lmo)	Luganda (lg)	Luo (luo)	Madurese (mad)
Magahi (mag)	Maithili (mai)	Makassar (mak)	Malagasy (mg)
Malay (Jawi Script) (ms-Arab)	Mam (mam)	Mandeali (mjl)	Manx (gv)
Mapudungun (arn)	Marshallese (mh)	Marwadi (mwr)	Mauritian Creole (mfe)
Meadow Mari (chm)	Meiteilon (Manipuri) (mni-Mtei)	Mewari (mtr)	Minang (min)
Mizo (lus)	Modern Standard Arabic (ar)	Moorõ0e9 (mos)	Morrocan Arabic (ar-MA)
Mundari (Devanagari script) (unr-Deva)	NKo (bm-Nkoo)	Navajo (nv)	Ndau (ndc-ZW)
Nepalbhasa (Newari) (new)	Nepali (ne)	Nigerian Pidgin (pcm)	Nimadi (noe)
North Levantine Arabic (apc)	North Ndebele (nd)	Northern Sami (se)	Nuer (nus)
Occitan (oc)	Oromo (om)	Ossetian (os)	Pangasinan (pag)
Papiamento (pap)	Polish (pl)	Q'eqchi' (kek)	Quechua (qu)
Rohingya (Latin script) (rhg-Latn)	Romani (rom)	Rundi (rn)	Russian (ru)
Sambalpuri (spv)	Sango (sg)	Sanskrit (sa)	Santali (Latin Script) (sat-Latn)
Saraiki (skr)	Sepedi (nso)	Sesotho (st)	Seychellois Creole (crs)
Shan (shn)	Sherpa (Tibetan script) (xsr-Tibt)	Shina (scl)	Shona (sn)
Sicilian (scn)	Silesian (szl)	Sindhi (Devanagari script) (sd-Deva)	Somali (so)
South Ndebele (nr)	Spanish (es)	Sudanese Arabic (Deprecated BCP) (apd)	Surgujia (sgj)
Surjapuri (sjp)	Susu (sus)	Swahili (sw)	Swati (ss)
Sylheti (syl)	Tahitian (ty)	Tamazight (Latin Script) (ber-Latn)	Tamazight (Tifinagh Script) (ber)
Tetum (tet)	Thai (th)	Tibetan (bo)	Tigrinya (ti)
Tiv (tiv)	Tok Pisin (tpi)	Tonga (Tonga Islands) (to)	Tsonga (ts)
Tswana (tn)	Tulu (tcy)	Tumbuka (tum)	Tunisian Arabic (aeb)
Turkish (tr)	Tuvan (tyv)	Twi (ak)	Udmurt (udm)
Venda (ve)	Venetian (vec)	Vietnamese (vi)	Wagdi (wbr)
Waray (Philippines) (war)	West Circassian (ady)	Wolof (wo)	Xhosa (xh)
Yakut (sah)	Yoruba (yo)	Yucatec Maya (yua)	Zapotec (zap)

Table 6 | Languages from English

Albanian (sq)	Arabic (Egypt) (ar-EG)	Armenian (hy)	Bangla (bn)	Basque (eu)
Belarusian (be)	Bosnian (bs)	Bulgarian (bg)	Burmese (my)	Catalan (ca)
Chinese (Taiwan) (zh-TW)	Corsican (co)	Croatian (hr)	Czech (cs)	Danish (da)
Estonian (et)	Filipino (fil)	Finnish (fi)	French (Canada) (fr-CA)	Galician (gl)
Greek (el)	Gujarati (gu)	Haitian Creole (ht)	Hawaiian (haw)	Hebrew (he)
Hmong (hmn)	Hungarian (hu)	Icelandic (is)	Inuktut (Latin) (iu-Latn)	Irish (ga)
Javanese (jv)	Kannada (kn)	Kazakh (kk)	Khmer (km)	Kyrgyz (ky)
Lao (lo)	Latvian (lv)	Lithuanian (lt)	Luxembourgish (lb)	Macedonian (mk)
Malay (ms)	Malayalam (ml)	Maltese (mt)	Marathi (mr)	Mongolian (mn)
Norwegian (no)	Persian (fa)	Portuguese (Brazil) (pt-BR)	Portuguese (Portugal) (pt-PT)	Punjabi (pa)
Romanian (ro)	Samoan (sm)	Santali (Ol Chiki script) (sat)	Scottish Gaelic (gd)	Serbian (Cyrillic) (sr-Cyrl)
Serbian (Latin) (sr-Latn)	Sinhala (si)	Slovak (sk)	Slovenian (sl)	Sundanese (su)
Swahili (Kenya) (sw-KE)	Swahili (Tanzania) (sw-TZ)	Swedish (sv)	Tajik (tg)	Tamil (ta)
Telugu (te)	Tshiluba (Luba-Lulua) (lua)	Ukrainian (uk)	Urdu (ur)	Uyghur (ug)

Table 7 | Non-English language pairs

Amharic (am)↔Arabic (ar)	Amharic (am)↔Mandarin Chinese (zh)	Arabic (ar)↔Swahili (sw)
Cantonese (yue)↔Mandarin Chinese (zh)	Cantonese (yue)↔Taiwanese Mandarin (zh-Hant)	Chinese (zh-CN)→Japanese (ja)
Czech (cs)→German (de)	Czech (cs)→Ukrainian (uk)	Mandarin Chinese (zh)↔Swahili (sw)