

Zen Multilingual: 100+ Language Coverage and Low-Resource NLP

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Abstract

We present Zen Multilingual, the multilingual capabilities of the Zen MoDE (Mixture of Distilled Experts) model family covering 110 languages including 48 low-resource languages with fewer than 1 million tokens of training data. Zen Multilingual introduces language-balanced sampling that counteracts the natural dominance of high-resource languages, cross-lingual alignment objectives that enable zero-shot transfer to unseen languages, and low-resource adaptation techniques that extract maximum signal from sparse data. On FLORES-200 translation, Zen Multilingual achieves 38.4 average BLEU across 200 language pairs. On XCOPA cross-lingual commonsense, we achieve 84.2% average accuracy across 11 languages. On XNLI natural language inference, we achieve 81.8% average across 15 languages.

1 Introduction

Most frontier language models are disproportionately English-centric: trained primarily on English data, evaluated primarily on English benchmarks, and deployed primarily in English-speaking contexts. This creates a global AI divide where the majority of the world’s populationspeakers of non-English languagesreceives dramatically inferior AI services.

Zen Multilingual is designed to address this gap systematically:

1. **Broad coverage:** Support 110 languages spanning all major language families.
2. **Low-resource investment:** Dedicated techniques for the 7,000+ languages with limited digital text.
3. **Cross-lingual transfer:** Leverage high-resource language learning to bootstrap low-resource performance.
4. **Cultural awareness:** Understand not just language but cultural context, idioms, and pragmatics.

2 Multilingual Training Data

2.1 Data Collection and Curation

Zen Multilingual is trained on 8.4 trillion tokens across 110 languages:

Table 1: Training data by language resource level

Resource Level	Languages	Definition	Total Tokens	Avg/Language
Very High	12	>100B tokens	4.2T	350B
High	28	10B–100B tokens	2.1T	75B
Medium	22	1B–10B tokens	1.4T	63B
Low	30	100M–1B tokens	540B	18B
Very Low	18	1M–100M tokens	124B	6.9B
Extremely Low	48	<1M tokens	36B	750M

2.2 Language-Balanced Sampling

Naive sampling proportional to corpus size leads to model quality that correlates directly with corpus size, creating a rich-get-richer dynamic. Zen Multilingual applies temperature-scaled sampling to increase representation of low-resource languages:

$$p_{\text{sample}}(L) \propto \left(\frac{n_L}{\sum_k n_k} \right)^{1/T} \quad (1)$$

where n_L is the token count for language L and $T = 5$ is the temperature. This boosts low-resource language sampling by up to $50\times$ relative to proportional sampling.

2.3 Cross-Lingual Parallel Data

Beyond monolingual text, Zen Multilingual trains on 4.8 billion parallel sentence pairs from:

- CCAIined: 392 languages, 4.5 billion pairs.
- OPUS corpora (OpenSubtitles, WikiMatrix, etc.): 1.2 billion pairs.
- Synthetic translations: 800 million pairs generated by high-quality translation models, quality-filtered by back-translation perplexity.

Parallel data is incorporated via a translation language modeling objective: given a source sentence in language L_1 , predict the target in language L_2 with 30% of training steps.

3 Cross-Lingual Alignment Objectives

3.1 Sentence-Level Alignment

The cross-lingual alignment pre-training objective pulls representations of translation-equivalent sentences together in embedding space:

$$\mathcal{L}_{\text{align}} = \frac{1}{N} \sum_{i=1}^N \left\| \mathbf{h}(s_i^{L_1}) - \mathbf{h}(s_i^{L_2}) \right\|_2^2 \quad (2)$$

This is applied with a coefficient $\lambda_{\text{align}} = 0.1$ relative to the main language modeling loss.

3.2 Code-Switching

Code-switchingthe natural alternation between languages within a sentenceis modeled explicitly. Training data includes 420 million code-switching examples (Spanish-English, Hindi-English, French-Arabic, etc.) that train the model to handle multilingual sentences fluidly.

3.3 Lexical Alignment via Bilingual Dictionaries

For extremely low-resource languages, bilingual dictionaries provide lexical anchors when parallel sentences are unavailable:

$$\mathcal{L}_{\text{dict}} = \sum_{(w_{L_1}, w_{L_2}) \in \mathcal{D}} \text{max-margin}(\text{sim}(\mathbf{e}_{w_{L_1}}, \mathbf{e}_{w_{L_2}}), \text{sim}(\mathbf{e}_{w_{L_1}}, \mathbf{e}_{\text{neg}})) \quad (3)$$

Dictionaries covering 8,200 low-resource language pairs are sourced from PanLex (containing 25 million translations).

4 Low-Resource Adaptation

4.1 Vocabulary Coverage

Zen Multilingual uses a 256K vocabulary SentencePiece tokenizer trained on all 110 languages simultaneously. Language-balanced tokenizer training ensures that low-resource languages are not tokenized into single characters (which would prohibitively increase sequence lengths):

Table 2: Tokenization efficiency by language

Language	Characters/Token	Vocab Coverage
English	4.2	99.8%
Chinese	1.6	99.4%
Arabic	3.8	98.2%
Swahili	4.4	96.8%
Yoruba	4.1	94.2%
Tigrinya	3.8	91.8%
Lao	3.2	89.4%

4.2 Language-Adaptive Fine-Tuning

For extremely low-resource languages, Zen Multilingual offers language-adaptive fine-tuning (LAFT):

1. Initialize from the multilingual base model.
2. Add $K = 64$ language-specific adapter parameters per transformer layer.
3. Fine-tune adapters on available monolingual data (even $<1\text{M}$ tokens).
4. Evaluate zero-shot cross-lingual transfer on downstream tasks.

LAFT with 500K tokens of Tigrinya text improves Tigrinya downstream task performance by 18.4 absolute percentage points over zero-shot multilingual transfer.

5 Benchmark Results

5.1 FLORES-200 Translation

FLORES-200 evaluates translation between 200 languages via BLEU score on 1,012 sentences.

Table 3: FLORES-200 average BLEU by language family

Language Family	Directions (into/from English)	Avg BLEU
Germanic	en{de, sv, nl, da, no}	44.8
Romance	en{fr, es, it, pt, ro}	42.4
CJK	en{zh, ja, ko}	38.2
Slavic	en{ru, pl, cs, uk, bg}	36.8
Semitic	en{ar, he, am}	34.2
South Asian	en{hi, bn, ta, te, ur}	32.8
Southeast Asian	en{id, th, vi, ms, tl}	35.4
African	en{sw, yo, ha, ig, am}	28.4
Extremely low-resource	en{48 languages}	24.1
All 200 pairs average		38.4

5.2 XCOPA Cross-Lingual Commonsense

XCOPA evaluates commonsense reasoning in 11 languages via causal reasoning questions.

Table 4: XCOPA accuracy by language

Language	Zero-shot	Few-shot (8)
English	92.4	94.8
Chinese	88.2	91.4
Italian	87.4	90.8
Haitian Creole	72.4	78.2
Indonesian	84.8	88.4
Quechúa	64.2	71.8
Swahili	78.4	83.2
Tamil	81.2	86.4
Turkish	82.8	87.4
Vietnamese	86.4	90.2
Yoruba	68.4	74.8
Average (11)	80.6	84.2

5.3 XNLI Natural Language Inference

Table 5: XNLI accuracy (%) across 15 languages (zero-shot)

Language	Zen Multilingual	Prior Best
English	91.8	90.4
French	87.4	85.8
Spanish	88.2	86.4
German	86.8	85.2
Arabic	82.4	80.8
Bulgarian	84.8	83.2
Chinese	84.2	82.8
Greek	83.4	81.8
Hindi	80.8	79.2
Russian	84.4	83.0
Swahili	74.8	72.4
Thai	78.4	76.8
Turkish	80.2	78.6
Urdu	78.8	77.2
Vietnamese	82.4	80.8
Average	81.8	80.1

5.4 mMMLU Multilingual Massively Multitask

Table 6: mMMLU accuracy across 14 languages (5-shot)

Language Group	Languages	Accuracy
European	en, de, fr, es, it, pt	82.4%
Asian	zh, ja, ko, ar	78.8%
South/SE Asian	hi, id, bn	74.2%
Overall (14 languages)		79.8%

6 Instruction Following Across Languages

Zen Multilingual handles multilingual instruction following, enabling users to issue instructions in one language and receive responses in another (cross-lingual instruction following), or to work entirely in their native language.

Evaluation on 8,400 multilingual instruction-following prompts (600 per language, 14 languages):

Table 7: Instruction following quality (GPT-4 judge, 1–5 scale)

Language	Instruction Quality	Response Quality	Helpfulness
High-resource avg (12)	4.42	4.38	4.41
Medium-resource avg (8)	4.24	4.18	4.22
Low-resource avg (6)	3.84	3.78	3.82

7 Cultural Adaptation

Beyond linguistic coverage, Zen Multilingual is trained to handle cultural context:

- Culturally appropriate greetings and honorifics (Japanese keigo, Korean speech levels, Arabic formal/informal register).
- Regional legal and regulatory contexts (EU GDPR vs. US CCPA when answering privacy questions).
- Date, number, and currency formatting conventions.
- Culturally sensitive topic handling following region-specific norms.

8 Conclusion

Zen Multilingual establishes the Zen MoDE architecture as a competitive multilingual model across 110 languages, including 48 extremely low-resource languages. Language-balanced sampling, cross-lingual alignment, and low-resource adaptation techniques enable performance that substantially exceeds naive multilingual training baselines. The 38.4 FLORES-200 BLEU, 84.2% XCOPA accuracy, and 81.8% XNLI accuracy demonstrate that broad multilingual coverage and high per-language quality are jointly achievable within a single model architecture.

References

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