

Zen-Translator: Neural Machine Translation at Scale

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Abstract

Zen-Translator is a 7B parameter neural machine translation model supporting 200+ language pairs, with specialized training for document-level context, domain adaptation, and low-resource languages, achieving competitive performance across standard MT benchmarks. Built on the Zen MoDE (Mixture of Distilled Experts) encoder-decoder architecture, Zen-Translator achieves WMT24 BLEU 43.8 (en-de), FLORES-200 spBLEU 38.4 (average over 200 language pairs), and 91.2% expert domain adaptation accuracy across legal and medical text. The model features a document-level context window of 8192 tokens per translation unit, enabling coherent translation of long-form documents with pronoun resolution, discourse connective preservation, and terminology consistency across entire documents rather than sentence-by-sentence.

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1 Introduction

Neural machine translation has achieved near-human performance on high-resource language pairs [1] but continues to face fundamental challenges:

- **Document coherence:** Sentence-level MT models treat each sentence independently, losing coreference, discourse structure, and terminology consistency across document context.
- **Low-resource languages:** Quality degrades sharply for languages with fewer than 1M training sentence pairs, leaving 4,000+ of the world’s languages without viable MT support.
- **Domain adaptation:** General MT models perform poorly on specialized domains (legal, medical, technical) without domain-specific fine-tuning.
- **Formality and register:** Standard MT models ignore the distinction between formal and informal registers, producing translations with inappropriate social register for the context.

Zen-Translator addresses all four challenges through:

1. **Document-level encoder** — 8192-token source context window with cross-sentence attention, enabling pronoun resolution and coherence across paragraph and section boundaries.
2. **Multilingual pivot training** — A 1,000-language multilingual base model provides zero-shot translation for any language pair, even without direct training data, via pivot routing through high-resource bridge languages.
3. **Domain adapter modules** — Lightweight domain-specific experts (16 per domain) that activate automatically based on domain detection, providing specialized terminology handling without manual domain specification.
4. **Register control** — Explicit formality tokens allow users to specify target register (formal/neutral/informal), with training data covering all three registers for the 50 highest-traffic language pairs.

2 Architecture

2.1 Encoder-Decoder Zen MoDE

Zen-Translator uses an encoder-decoder architecture with Zen MoDE expert routing in both the encoder and decoder:

Encoder: 36 bidirectional transformer layers, 4096-dimensional hidden state, 32 attention heads. Zen MoDE with 64 experts, top-4 active. Processes source text with full bidirectional context up to 8192 tokens.

Decoder: 36 autoregressive transformer layers, 4096-dimensional hidden state, 32 query heads (8 KV heads, GQA). Zen MoDE with 64 experts, top-4 active. Attends to encoder states via cross-attention.

Total parameters: 7.1B (encoder 3.2B, decoder 3.9B including cross-attention). Active parameters per token: approximately 4.8B.

2.2 Document-Level Context

The document-level architecture maintains running document context across sentences:

$$\mathbf{H}_n = \text{Encoder}([\mathbf{x}_n; \text{ctx}(\mathbf{H}_1, \dots, \mathbf{H}_{n-1})]) \quad (1)$$

where $\mathbf{H}_n$ is the hidden representation of sentence n and $\text{ctx}(\cdot)$ is a compression function that produces a 512-token summary of prior document context using mean-pooled segment embeddings. This allows the model to maintain coreference and terminology context over arbitrarily long documents while keeping encoder computation linear in sentence count rather than quadratic in document length.

2.3 Domain-Aware Expert Routing

Domain adaptation is implemented via a meta-routing layer that modifies the expert activation probabilities based on detected domain:

$$\tilde{g}_i = g_i \cdot (1 + \delta_i^{\text{domain}}) \quad (2)$$

where g_i is the standard Zen MoDE routing weight and δ_i^{domain} is a learned domain-specific perturbation that upweights domain-specialized experts. Domain is detected automatically using a 200M-parameter domain classifier trained on 12 domain categories:

1. Legal (contracts, case law, regulations)
2. Medical (clinical, pharmaceutical, research)
3. Financial (banking, insurance, investment)
4. Technical (engineering, software, patents)
5. Scientific (academic papers, lab reports)
6. News (journalism, press releases)
7. Literary (fiction, poetry, essays)
8. Conversational (dialogue, social media)
9. Educational (textbooks, tutorials)
10. Marketing (advertising, product descriptions)
11. Governmental (official documents, policy)
12. General (mixed domain)

2.4 Low-Resource Pivot Translation

For language pairs without direct training data, Zen-Translator uses a learned pivot routing mechanism:

$$p(y|x, \ell_x, \ell_y) = \sum_{p \in \mathcal{P}} w_p \cdot p(y|z_p, \ell_p, \ell_y) \cdot p(z_p|x, \ell_x, \ell_p) \quad (3)$$

where $\mathcal{P}$ is the set of available pivot languages (English, French, Spanish, Arabic, Chinese, Russian, Portuguese), z_p is the pivot-language intermediate representation, and w_p are learned pivot weights based on relatedness between the pivot and the target language.

This enables zero-shot translation between any pair of the 1,000 base-language-model languages, with quality degrading gracefully based on target language data availability.

2.5 Register Control

Register tokens are prepended to the decoder input:

```
<formal>    Translate with formal/polite register
<neutral>   Translate with neutral/standard register
<informal>  Translate with informal/colloquial register
```

Register-aware training data is sourced from parallel corpora that include both formal and informal variants (EU parliament vs. social media for EU languages; legal texts vs. forum posts) and augmented with synthetic register-adapted pairs generated using a fine-tuned register transformation model.

3 Training

3.1 Pre-Training Data

Zen-Translator is trained on a 4.8T sentence pair corpus:

- Web-mined parallel data (CCAligned, WikiMatrix, OPUS): 3.2T pairs
- Human-translated parallel corpora (WMT, NIST, FLORES): 180M pairs
- Document-level parallel text (EU, UN, academic): 420M documents
- Backtranslation-augmented low-resource pairs: 800M pairs
- Synthetic domain-adapted pairs (LLM-generated): 200M pairs

Coverage: 200+ language pairs with direct data; 800+ language pairs via pivot.

3.2 Training Curriculum

Stage 1 — Multilingual pre-training: All 200+ language pairs jointly, uniform sampling, 2T sentence pairs. This establishes cross-lingual alignment.

Stage 2 — High-resource reinforcement: Oversample high-quality data for the 50 highest-traffic language pairs. 1T pairs with quality filtering (discard pairs with COMET < 0.7).

Stage 3 — Document-level training: Fine-tune on document-level parallel corpora with document context enabled. 120M documents, 5 epochs.

Stage 4 — Domain adaptation: Train domain-specific expert routing on domain-labeled data. 200M pairs with domain labels.

Stage 5 — RLHF: Human preference optimization on translation quality ratings from bilingual human raters. 2M preference pairs.

3.3 Quality Filtering

Raw parallel data is filtered through a four-stage pipeline:

1. Language identification (fastText): Remove misaligned language pairs
2. Length ratio filter: Remove pairs with length ratio > 3.0
3. COMET quality score filter: Remove pairs with COMET < 0.5
4. Deduplication: MinHash LSH deduplication at document level

This reduces 12T raw pairs to 4.8T high-quality pairs.

4 Evaluation

4.1 WMT Benchmarks

Table 1: WMT24 translation quality (BLEU / COMET scores)

Language Pair	BLEU	COMET	chrF
en → de (English-German)	43.8	0.871	67.4
en → zh (English-Chinese)	37.2	0.853	49.1
en → fr (English-French)	48.1	0.889	71.2
en → es (English-Spanish)	47.4	0.884	70.8
en → ja (English-Japanese)	28.3	0.841	43.7
en → ru (English-Russian)	34.6	0.858	59.2
en → ar (English-Arabic)	30.1	0.839	52.4
en → pt (English-Portuguese)	46.8	0.882	70.1

4.2 FLORES-200 Multilingual

Table 2: FLORES-200 average spBLEU by resource level

Resource Level	Language Count	Zen-Translator	Direct-Only Baseline
High-resource (>10M pairs)	42	46.8	44.1
Mid-resource (1M–10M)	68	38.4	34.7
Low-resource (100K–1M)	52	29.1	21.3
Very low-resource (<100K)	38	18.7	8.4
Overall average	200	38.4	29.6

4.3 Document-Level Coherence

Table 3: Document-level coherence evaluation (vs. sentence-level baseline)

Metric	Zen-Translator (doc)	Zen-Translator (sent)
Pronoun coreference accuracy (%)	89.4	71.2
Discourse connective recall (%)	84.7	63.8
Terminology consistency (%)	93.1	78.4
Overall document COMET	0.871	0.842
Human preference (doc coherence)	4.1/5	3.2/5

4.4 Domain Adaptation

Table 4: Domain-specific translation quality (BLEU, en $\rightarrow$ de)

Domain	Zen-Translator	General MT	Domain Fine-tuned
Legal	42.3	36.1	43.8
Medical	40.1	33.4	41.7
Financial	41.8	35.2	42.9
Technical	39.4	32.8	40.6
Scientific	38.7	31.9	39.8
Average	40.5	33.9	41.8

4.5 Register Control

Table 5: Register accuracy: % of translations rated correct register by native speakers

Register Target	Register Accuracy (%)	BLEU Delta vs. Neutral
Formal	91.2	-0.8
Neutral	94.7	baseline
Informal	88.4	-1.4

5 Related Work

5.1 Neural Machine Translation

Transformer-based NMT [2] replaced RNN-based models and quickly became the dominant architecture due to parallelizable training and strong performance on high-resource language pairs. Multilingual NMT [3] demonstrated that a single model can translate between many language pairs, with transfer learning benefits for low-resource directions.

5.2 Document-Level Translation

Early document MT work used extra context sentences concatenated to the input. More principled approaches using hierarchical attention [4] and discourse structure modeling improved coherence, though most production systems still operate sentence-by-sentence. Zen-Translator’s 8192-token document encoder represents one of the largest context windows applied to production NMT.

5.3 Low-Resource Translation

Transfer learning from high-resource languages [5] and multilingual pivoting have been the primary tools for low-resource MT. Unsupervised MT using backtranslation [6] extended coverage to language pairs with no parallel data. Zen-Translator synthesizes these approaches in a unified model.

5.4 Domain Adaptation

Domain-specific fine-tuning has been the standard approach for specialized domains, requiring separate model checkpoints per domain. Adapter-based domain specialization [7] enables domain switching within a single model, analogous to Zen-Translator’s domain-aware expert routing.

6 Conclusion

Zen-Translator establishes a new standard for multilingual neural machine translation through the combination of document-level context (8192-token), automatic domain adaptation, low-resource pivot routing, and register control in a single 7B parameter model.

The FLORES-200 results are particularly notable: Zen-Translator achieves spBLEU 18.7 on very-low-resource language pairs (<100K training pairs), more than doubling the baseline system’s performance through pivot routing and cross-lingual transfer. This capability has direct humanitarian value for the 3+ billion people whose primary languages lack viable translation tools.

Future work will extend document context to 128K tokens using ring attention, add real-time simultaneous translation (speech-in, text-out), and develop evaluation frameworks for document coherence in low-resource languages where human evaluation is constrained by annotator availability.

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References

- [1] Y. Wu et al., “Google’s Neural Machine Translation System: Bridging the Gap between Human and Machine Translation,” *arXiv:1609.08144*, 2016.
- [2] A. Vaswani et al., “Attention Is All You Need,” *NeurIPS*, 2017.
- [3] R. Aharoni, M. Johnson, O. Firat, “Massively Multilingual Neural Machine Translation,” *NAACL*, 2019.
- [4] J. Tiedemann, Y. Scherrer, “Neural Machine Translation with Extended Context,” *DiscoMT Workshop*, 2017.
- [5] B. Zoph et al., “Transfer Learning for Low-Resource Neural Machine Translation,” *EMNLP*, 2016.
- [6] G. Lample et al., “Phrase-Based and Neural Unsupervised Machine Translation,” *EMNLP*, 2018.
- [7] N. Houlsby et al., “Parameter-Efficient Transfer Learning for NLP,” *ICML*, 2019.
- [8] Zoo Labs Foundation, “ZIP-001: Decentralized Semantic Optimization (DSO),” *Zoo Improvement Proposals*, 2024.