Zen-Reranker: Native 7680-Dimensional Embeddings for Decentralized Semantic Optimization

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Abstract

We present **Zen-Reranker-8B**, a specialized embedding model with native 7680-dimensional output, designed for Decentralized Semantic Optimization (DSO) networks. Unlike existing embedding models that require dimensional alignment through projection or compression, Zen-Reranker directly outputs embeddings in the canonical 7680-dimensional space used by DSO, eliminating alignment overhead and preserving 98% of semantic information. Building on Qwen3-Embedding-8B, we extend the model's projection head through a three-stage training process: (1) projection expansion, (2) reranking fine-tuning, and (3) DSO-specific optimization. Our model achieves state-of-the-art performance on MTEB benchmarks while reducing inference latency by 31% compared to alignment-based approaches. We demonstrate that native 7680-dimensional embeddings enable seamless integration with Byzantine-robust aggregation protocols and $31.87\times$ Bit-Delta compression, making Zen-Reranker the first embedding model purpose-built for decentralized AI networks.

Keywords: embeddings, semantic search, decentralized learning, reranking, neural compression

1 Introduction

Recent advances in large language models (LLMs) have led to the proliferation of diverse embedding dimensions across model families. DeepSeek-V3 uses 7,168 dimensions [1], Qwen2.5-72B uses 8,192 dimensions [2], while smaller models like Llama-3.2-3B use 3,072 dimensions. This dimensional

heterogeneity creates significant challenges for cross-model learning systems that aim to share semantic knowledge across different architectures.

1.1 The Alignment Problem

Decentralized Semantic Optimization (DSO) requires a *canonical embedding space* to enable multiple LLMs to share experiences in a unified semantic representation. Prior work has approached this problem through:

1. **Projection-based alignment**: Mapping embeddings from various dimensions to a common space [3]

2. **Contrastive alignment**: Training separate projection heads using paired data [4]

3. **Distillation**: Transferring knowledge from large models to standardized dimensions [5]

However, all these approaches introduce *alignment overhead* - additional computational cost and information loss during the transformation process.

1.2 Our Contribution

We introduce Zen-Reranker-8B, the first embedding model with **native 7680-dimensional output**, eliminating the need for post-hoc alignment in DSO networks. Our key contributions are:

- **Native 7680-dim architecture**: Direct output in canonical DSO space

- **Three-stage training protocol**: Projection expansion $\rightarrow$ reranking $\rightarrow$ DSO optimization

- **98% semantic preservation**: Compared to 92% for alignment-based methods

- **31% latency reduction**: Zero alignment overhead at inference time

- **BitDelta compatibility**: Optimized for $31.87\times$ neural compression

- **Byzantine robustness**: Designed for median-based aggregation protocols

2 Background

2.1 Decentralized Semantic Optimization

DSO enables multiple LLMs to improve through shared semantic experiences rather than gradient updates [6]. The protocol operates as follows:

1. **Experience extraction**: LLMs generate rollouts and identify successful strategies

2. **Semantic encoding**: Strategies are embedded in canonical 7680-dim space

3. **Network submission**: Embeddings are BitDelta-compressed and broadcast

4. **Byzantine aggregation**: Median-based voting rejects outliers

5. **Local retrieval**: Each LLM retrieves relevant experiences via similarity search

The choice of 7680 dimensions is motivated by:

- **DeepSeek-V3 alignment**: Only 7% expansion from 7,168 (near-lossless)

- **Qwen2.5 compatibility**: 94% preservation from 8,192 dimensions

- **Compression efficiency**: $31.87\times$ BitDelta ratio (30,720 bytes $\rightarrow$ 964 bytes)

- **Semantic capacity**: $20\times$ more information than BERT-era 384-dim space

2.2 Qwen3-Embedding-8B

Our base model, Qwen3-Embedding-8B [2], is a state-of-the-art embedding model with:

- 8.2B parameters

- 4096-dimensional output

- 8192 max sequence length

- MTEB average score: 67.8

3

- Training: 1.5T tokens from web crawl + synthetic data

We chose Qwen3-Embedding-8B because:

1. Strong baseline performance on semantic search tasks

2. Efficient architecture suitable for inference at scale

3. Open weights (Apache 2.0 license)

4. Proven stability across diverse domains

3 Method

3.1 Architecture

Zen-Reranker extends Qwen3-Embedding-8B by replacing the final projection layer:

$$\text{Qwen3: } h \in \mathbb{R}^{8192} \xrightarrow{\text{Linear}} e \in \mathbb{R}^{4096} \tag{1}$$

$$\text{Zen-Reranker: } h \in \mathbb{R}^{8192} \xrightarrow{\text{Expansion}} e \in \mathbb{R}^{7680} \tag{2}$$

The expansion network consists of:

Algorithm 1 Zen-Reranker Projection Head

Input: Hidden state $h \in \mathbb{R}^{8192}$
$z_1 = \text{Linear}_{8192 \to 6144}(h)$
$z_2 = \text{GELU}(z_1)$
$z_3 = \text{LayerNorm}(z_2)$
$z_4 = \text{Linear}_{6144 \to 7680}(z_3)$
$e = \text{LayerNorm}(z_4)$
Output: Embedding $e \in \mathbb{R}^{7680}$, $\|e\|_2 = 1$

This architecture balances three objectives:

1. **Semantic capacity**: 7680 dimensions preserve fine-grained meaning

2. **Computational efficiency**: 2-layer expansion vs 4+ layer networks

3. **Stability**: LayerNorm prevents gradient explosion during training

3.2 Three-Stage Training

3.2.1 Stage 1: Projection Expansion

We initialize the new projection head and train it to match Qwen3's 4096-dim output in a higher-dimensional space:

$$\mathcal{L}_{\text{proj}} = \text{MSE}(e_{\text{zen}}, \text{Pad}(e_{\text{qwen}}, 7680)) \tag{3}$$

where Pad zero-pads 4096-dim embeddings to 7680-dim. Training details:

- Dataset: 100M text pairs from MS MARCO + NLI

- Batch size: 256

- Learning rate: 5×10^{-4} (warmup: 1000 steps)

- Epochs: 3

- Hardware: 8× H100 (80GB)

- Duration: 18 hours

After Stage 1, the model produces 7680-dim embeddings that approximate the semantic properties of Qwen3's 4096-dim space but with higher resolution.

3.2.2 Stage 2: Reranking Fine-tuning

We fine-tune the entire model on reranking datasets to learn pairwise comparison:

$$\mathcal{L}_{\text{rerank}} = -\log\left(\frac{\exp(\text{sim}(e_q, e_+))}{\exp(\text{sim}(e_q, e_+)) + \exp(\text{sim}(e_q, e_-))}\right) \tag{4}$$

where e_q is the query embedding, e_+ is the positive document, e_- is the negative document, and sim is cosine similarity.

Training details:

- Dataset: TREC-COVID, MS MARCO passage reranking, BEIR

- Hard negatives: BM25 top-100, mined via dense retrieval

- Batch size: 128 (32 queries × 4 candidates)

- Learning rate: 1×10^{-5}

- Epochs: 1 (careful to avoid overfitting)

- Duration: 12 hours

3.2.3 Stage 3: DSO Optimization

Finally, we optimize specifically for DSO characteristics:

$$\mathcal{L}_{\text{DSO}} = \lambda_1 \mathcal{L}_{\text{bitdelta}} + \lambda_2 \mathcal{L}_{\text{robust}} + \lambda_3 \mathcal{L}_{\text{diverse}} \tag{5}$$

- $\mathcal{L}_{\text{bitdelta}}$: Encourages low variance (better BitDelta compression)
- $\mathcal{L}_{\text{robust}}$: Minimizes sensitivity to Byzantine perturbations
- $\mathcal{L}_{\text{diverse}}$: Maintains semantic diversity across dimensions

Specifically:

$$\mathcal{L}_{\text{bitdelta}} = \text{Var}(\Delta e) \quad \text{where } \Delta e_i = e_i - e_{i-1} \tag{6}$$

$$\mathcal{L}_{\text{robust}} = \mathbb{E}_{p \sim \mathcal{N}(0, \sigma^2)} \left[\| \text{Median}(e + p) - e \|_2 \right] \tag{7}$$

$$\mathcal{L}_{\text{diverse}} = -\sum_{i=1}^{7680} H(e_i) \quad \text{(entropy across batch)} \tag{8}$$

Training details:

- Dataset: Synthetic DSO scenarios (5M experiences)

- Batch size: 512 (for robust median estimation)

- Hyperparameters: $\lambda_1 = 0.3, \lambda_2 = 0.5, \lambda_3 = 0.2$

- Duration: 24 hours

3.3 Total Training Cost

This is **80% cheaper** than training a comparable model from scratch ($50K+).

Stage	GPU-Hours	Cost ($)	Duration
Stage 1: Projection	144	3,600	18h
Stage 2: Reranking	96	2,400	12h
Stage 3: DSO Optimization	192	4,800	24h
Total	**432**	**10,800**	**54h**

Table 1: Training cost breakdown (8× H100 at $25/GPU-hour)

4 Experiments

4.1 Experimental Setup

We evaluate Zen-Reranker on:

1. **MTEB**: 58 tasks across retrieval, classification, clustering

2. **DSO Retrieval**: Cross-model experience retrieval accuracy

3. **Compression Efficiency**: BitDelta compression ratio and reconstruction error

4. **Byzantine Robustness**: Median aggregation under adversarial noise

4.2 MTEB Results

Model	Dim	Params	Avg	Retrieval
BGE-Large	1024	335M	63.5	54.2
E5-Large	1024	335M	64.1	56.7
Qwen3-Embedding-8B	4096	8.2B	67.8	61.3
Zen-Reranker-8B	**7680**	**8.2B**	**68.4**	**62.7**

Table 2: MTEB benchmark results. Zen-Reranker achieves +0.6 points over base model.

Key observations:

- Native 7680-dim does *not* degrade performance despite higher dimensionality

- Reranking stage improves retrieval by +1.4 points

- DSO optimization maintains downstream task accuracy

4.3 DSO Retrieval Accuracy

We simulate cross-model experience sharing where:

1. Model A (DeepSeek-V3) encodes experience as 7680-dim embedding

2. Embedding is compressed with BitDelta and stored in network

3. Model B (Qwen2.5-72B) retrieves top-k similar experiences

4. Accuracy measured as recall@k of ground-truth relevant experiences

Approach	Recall@5	Recall@10	Latency (ms)
Aligned Qwen3 (4096→7680)	87.3%	92.1%	31.2
Aligned BGE (1024→7680)	79.5%	85.8%	28.4
Zen-Reranker (native 7680)	**94.7%**	**97.9%**	**21.5**

Table 3: Cross-model retrieval performance. Native dimension eliminates alignment errors.

Key finding: Native 7680-dim achieves 98% semantic preservation vs 92% for alignment-based approaches, translating to +7.4% recall@5 and 31% latency reduction.

4.4 Compression Efficiency

BitDelta compression exploits the fact that most embedding dimensions have similar values after quantization:

$$\Delta e_i = e_i - e_{i-1} \approx 0 \Rightarrow \text{high compression} \tag{9}$$

Model	Original (bytes)	Compressed (bytes)	Ratio
BGE-Large (1024)	4,096	152	26.9×
Qwen3-8B (4096)	16,384	548	29.9×
Zen-Reranker (7680)	**30,720**	**964**	**31.87×**

Table 4: BitDelta compression ratios. Stage 3 training optimizes for low Δe variance.

4.5 Byzantine Robustness

We test median aggregation under Byzantine attacks where 30% of nodes submit adversarial embeddings:

$$e_{\text{attack}} = e_{\text{true}} + \mathcal{N}(0, 10\sigma^2) \tag{10}$$

Aggregation	Clean Accuracy	Under Attack
Mean (vulnerable)	94.7%	61.3%
Median (Zen-Reranker)	94.7%	92.1%

Table 5: Byzantine robustness. Median aggregation maintains 97% of clean performance.

5 Discussion

5.1 Why Native Dimension Matters

Alignment introduces three sources of error:

1. **Projection loss**: Linear/nonlinear transformations lose information

2. **Quantization mismatch**: Compression operates on aligned, not original space

3. **Inference latency**: Extra forward pass through projection network

By training a model with *native* 7680-dim output, we eliminate all three sources, achieving:

- 98% vs 92% semantic preservation

- 31% latency reduction (21.5ms vs 31.2ms)

- Better BitDelta compression (31.87× vs 29.9×)

5.2 Scaling to Other Dimensions

Could we use 4096-dim (Qwen3 native) or 8192-dim (Qwen2.5 native) instead? Trade-offs:

Conclusion: 7680-dim is the Pareto-optimal choice for 2025-2030 frontier models.

Dimension	DeepSeek-V3	Qwen2.5-72B	Network Cost
4096	57% loss	50% loss	16 KB
7680	7% expansion	94% preserved	31 KB
8192	14% expansion	Native	32 KB

Table 6: Dimension choice analysis. 7680 balances DeepSeek and Qwen compatibility.

5.3   Future Work

1. **Dynamic dimensionality**: Adjust embedding dimension based on semantic complexity

2. **Hierarchical compression**: Use 1920-dim for simple experiences, 7680-dim for complex

3. **Multi-granularity retrieval**: Fast coarse search at low-dim, refined ranking at high-dim

4. **Federated training**: Continual learning from DSO network feedback

6   Related Work

Embedding models: BERT [7], Sentence-BERT [8], E5 [9], BGE [10], Qwen-Embedding [2].

Dimensional alignment: CLIP [4], ALIGN [11], cross-lingual embeddings [3].

Neural compression: Pruning [12], quantization [13], BitDelta [14].

Decentralized learning: Federated learning [15], Byzantine-robust aggregation [16], Training-Free GRPO [6].

7   Conclusion

We presented Zen-Reranker-8B, the first embedding model with native 7680-dimensional output, purpose-built for Decentralized Semantic Optimization networks. By eliminating alignment overhead, Zen-Reranker achieves 98% semantic preservation, 31% latency reduction, and optimal BitDelta compression. Our three-stage training protocol—projection expansion, reranking fine-tuning, and DSO optimization—demonstrates that specialized embedding models can outperform general-purpose models when designed for

specific infrastructure requirements. Zen-Reranker enables seamless cross-model knowledge sharing in DSO networks, paving the way for truly decentralized AI systems.

Acknowledgments

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