Dewey Long Context Embedding Model: A Technical Report

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Abstract

This technical report presents the training methodology and evaluation results of the opensource dewey_en_beta embedding model. The increasing demand for retrieval-augmented generation (RAG) systems and the expanding context window capabilities of large language models (LLMs) have created critical challenges for conventional embedding models. Current approaches often struggle to maintain semantic coherence when processing documents exceeding typical sequence length limitations, significantly impacting retrieval performance in knowledge-intensive applications. This paper presents dewey_en_beta, a novel text embedding model that achieves excellent performance on MTEB (Eng, v2)(Enevoldsen et al., 2025) and LongEmbed benchmark(Zhu et al., 2024) while supporting 128K token sequences. Our technical contribution centers on chunk alignment training, an innovative methodology that enables the simultaneous generation of localized chunk embeddings and global document-level representations through distillation (Zhang et al., 2025). Information regarding the model release can be found at https://huggingface.co/infgrad /dewey_en_beta.

1 Introduction

Text embedding models serve as fundamental components in contemporary information retrieval systems and retrieval-enhanced language models. While recent advancements in semantic representation learning have yielded considerable improvements, practical challenges remain in processing extended textual content. The sequence length capacity of embedding models presents an important technical consideration, as enhanced context processing could potentially improve document comprehension and facilitate more adaptable retrieval implementations.

In this technical report, inspired by late chunking(Günther et al., 2024) we present a preliminary investigation into chunk-alignment training strategies for text embedding models. This exploratory approach attempts to address the representation learning challenges associated with long-form documents through segment-level feature alignment. Our experimental framework demonstrates the feasibility of processing text sequences up to 128k tokens while preserving performance levels on standard evaluation benchmarks. The current implementation offers two operational modes: a conventional single-vector encoding scheme and an experimental multi-vector variant for extended context processing.

The primary contribution lies in developing a chunk-alignment training method (achieved by knowledge distillation) that attempts to extend existing embedding architectures to longer textual sequences. It should be emphasized that this represents an initial exploration rather than a definitive solution, with the current results suggesting potential pathways for further investigation. Our comparative evaluations indicate relatively balanced performance across conventional benchmarks and preliminary long-context test sets, though we acknowledge significant room for improvement in both theoretical framework and practical implementation.

2 Training Methodology

Selection of Base Model

After investigating many models, we select ModernBERT-Large(Warner et al., 2024) as the base model of dewey_en_beta. ModernBERT is a modernized bidirectional encoder-only Transformer model (BERT-style) pre-trained on 2 trillion tokens of English and code data with a native context length of up to 8,192 tokens. ModernBERT leverages recent architectural improvements:

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- Rotary Positional Embeddings (RoPE)(Su et al., 2023) for long-context support.
- Local-Global Alternating Attention(Team et al., 2024) for efficiency on long inputs.
- Unpadding and Flash Attention (Portes et al., 2023)(Zhang et al., 2024b)(Zeng et al., 2022) for efficient inference.

To scale ModernBERT's max length to 128k, we change the *global_rope_theta* to 73780400 according to (Men et al., 2024) and https://spaces.ac.cn/archives/10122.

Chunk-Alignment Training

Our model can generate three types of embeddings:

- CLS embedding: A CLS embedding in a BERT-like model. In our training process, it will learn the teacher model's embedding of the whole text.
- Chunk embeddings: The mean embeddings of chunk token embeddings. In our training process, it will learn the teacher model's embedding of each chunk.
- 3. Mean embedding: The mean embeddings of all token embeddings (excluding CLS, SEP, and prompt token embeddings). It is a special case of chunk embedding (i.e. the chunk is the whole text).

For a more comprehensive introduction of our model and distillation framework, we make the following definitions:

- teacher: a teacher embedding model with the function encode to encode texts to embeddings
- *cls_embed*, *chunk_embed*_i: CLS embedding and chunk embedding of i_{th} chunk in student model(i.e. the model to be trained)
- cls_teacher_embed, chunk_teacher_embedi as the whole text teacher embedding and chunk teacher embeddings
- s_x : The normalized vector representation of a text x produced by the student model.
- t_x: The vector representation of the same text x, produced by a teacher model.

- S_X: A matrix of normalized vector representations for a batch of text X produced by the student model.
- T_X : A corresponding matrix of vector representations for the same batch of text X, generated by a teacher model.

 $cls_teacher_embed$ and $chunk_teacher_embed_i$ can be obtained by the following equations:

 $cls_teacher_embed = teacher.encode(wholetext)$

$$chunk_embed_i = teacher.encode(chunk_i)$$

After getting cls and chunks embeddings of student and teacher model, we calculate $cosine_loss$ 1 and $similarity_loss$ 2 as the final training loss.

$$\mathcal{L}_{cosine_loss} = \sum_{x} 1 - s_x \cdot t_x. \tag{1}$$

$$\mathcal{L}_{similarity\ loss} = MSE(S_X S_X^T, T_X T_X^T)) \quad (2)$$

Implementation Details

We use Linq-Embed-Mistral(Kim et al., 2024) as our teacher model. We get unsupervised texts from Infinity-Instruct(of Artificial Intelligence , BAAI)(Zhao et al., 2024)(Zhang et al., 2024a) and fineweb-edu(Lozhkov et al., 2024). We take two strategies to split text to chunks:

- 1. Split Text by Word
- 2. RecursiveCharacterTextSplitter in langchain https://python.langchain.com/d ocs/introduction/

We chose to use the RecursiveCharacter-TextSplitter with 70% probability and the Split Text by Word with 30% probability. All the two strategies use a randomized chunk_size(from 64 to 500) and chunk_overlap(from $0.3*chunk_size$ to $0.6*chunk_size$).

We are training our model with about 10 million data (about 100 million chunks). The batch size is set to 64, and the learning rate is 1e-4 with a 2000-step warmup and linear decay. We use the StableAdamW optimizer(Wortsman et al., 2023), which improves upon AdamW(Loshchilov and Hutter, 2019) by adding Adafactor-style update clipping as a per-parameter learning rate adjustment. We total train 2 epochs. We set weight decay to zero. The max length of training data is 2048.

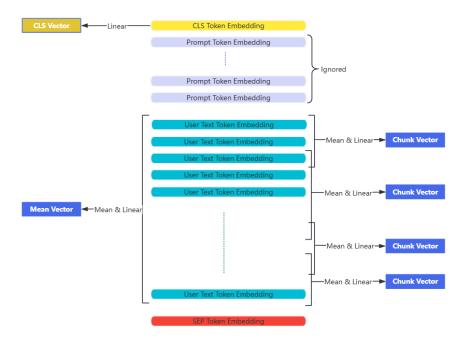


Figure 1: Model architecture

3 Experimental Results

English Text Embedding Benchmark

MTEB(eng, v2)(Enevoldsen et al., 2025) is a new English Massive Text Embedding Benchmark. This benchmark was created to account for the fact that many models have now been finetuned to tasks in the original MTEB, and contains tasks that are not as frequently used for model training. This way the new benchmark and leaderboard can give our users a more realistic expectation of models' generalization performance.

We evaluated our model's performance on this benchmark. As shown in 1, while our model supports a context length of 128k tokens, it still achieves competitive results, outperforming most models of comparable size and even some larger-scale models on this particular benchmark.

LongEmbed Benchmark

LongEmbed(Zhu et al., 2024) is a benchmark oriented at exploring models' performance on long-context retrieval. The benchmark comprises two synthetic tasks and four carefully chosen real-world tasks, featuring documents of varying length and dispersed target information.

As can be observed from 2, our model achieves reasonably good results with single-vector representation, while the performance is further improved to an optimal level when multi-vector representation is employed.

LoCoV1 Benchmark

LoCoV1 (Saad-Falcon et al., 2024): a novel 12-tasks benchmark constructed to measure long-context retrieval where chunking is not possible or not effective.

4 Conclusion

In this concise technical report, we present preliminary insights into the dewey model and its training methodology. The proposed approach employs chunk-alignment techniques combined with knowledge distillation, trained on extensive unsupervised data. Our experimental results demonstrate promising performance across both long-text and short-text evaluation benchmarks, though we acknowledge these findings represent early-stage research outcomes.

While observing moderate improvements through chunk-alignment implementation, we recognize substantial room for exploration and refinement in this methodology. This report records current training details and empirical observations, shared with the intention of inviting constructive feedback and collaborative investigation. We hope these preliminary findings might serve as a discussion catalyst within the research community, particularly regarding potential optimizations in alignment strategies and scalability enhancements.

Model	Zero-shot	Parameters	Dimensions	Max Tokens	Mean (Task)	Mean (TaskType)	Classification	Clustering	Pair Classification	Reranking	Retrieval	STS	Summarization
gemini-embedding-exp-03-07	95%	Unknown	3072	8192	73.3	67.67	90.05	59.39	87.7	48.59	64.35	85.29	38.28
jasper_en_vision_language_v1	56%	1B	8960	131072	71.41	66.65	90.27	60.52	88.14	50	56.05	84.37	37.19
gte-Qwen2-7B-instruct	NA	7B	3584	32768	70.72	65.77	88.52	58.97	85.9	50.47	58.09	82.69	35.74
stella_en_1.5B_v5	56%	1B	8960	131072	69.43	65.32	89.38	57.06	88.02	50.19	52.42	83.27	36.91
SFR-Embedding-2_R	85%	7B	4096	32768	69.82	65.31	90.54	59.39	88.09	48.99	53.75	80.86	35.54
Linq-Embed-Mistral	95%	7B	4096	32768	69.8	65.29	83	54.07	88.44	49.44	60.14	84.69	37.26
dewey_en_beta	95%	395M	2048	131072	0.68	63.30	81.83	51.75	86.82	46.35	56.32	84.21	35.79
gte-Qwen2-1.5B-instruct	NA	1B	8960	32768	67.2	63.26	85.84	53.54	87.52	49.25	50.25	82.51	33.94
GritLM-7B	95%	7B	4096	4096	67.07	63.22	81.25	50.82	87.29	49.59	54.95	83.03	35.65
GritLM-8x7B	95%	57B	4096	4096	66.16	62.42	79.98	51.48	85.23	49.22	52.46	82.93	35.65

Table 1: MTEB(eng, v2) results, rows are sorted in descending order by column Mean (TaskType)

Model	Zero-shot	Number of Parameters	Embedding Dimensions	Max Tokens	Mean (Task)	Mean (TaskType)	Retrieval
dewey_en_beta-MultiVectors	100%	395M	2048	131072	86.59	86.59	86.59
voyage-multilingual-2	100%	Unknown	1024	32000	79.17	79.17	79.17
voyage-law-2	100%	Unknown	1024	16000	78.85	78.85	78.85
dewey_en_beta-SingleVector	100%	395M	2048	131072	77.98	77.98	77.98
voyage-3	100%	Unknown	1024	32000	74.06	74.06	74.06
inf-retriever-v1	100%	7B	3584	32768	73.19	73.19	73.19

Table 2: LongEmbed results, rows are sorted in descending order by column Mean (TaskType)

dataset-name	bge-m3-8k	gte-modernbert-base-8k	Linq-Embed-Mistral-4k	Linq-Embed-Mistral-8k	SFR-Embedding-Mistral-8k	e5-mistral-7b-instruct-8k	dewey_en_beta-8k	dewey_en_beta_64k	dewey_en_beta_64k-multi-vectors
2wikimqa_test	0.9271	0.8658	0.8884	0.9067	0.8965	0.8901	0.8953	0.9051	0.9775
courtlistener_HTML_test	0.1933	0.2349	0.3551	0.3670	0.3647	0.3543	0.3415	0.3616	0.4775
courtlistener_Plain_Text_test	0.1888	0.2478	0.3675	0.3761	0.3679	0.3579	0.3377	0.3485	0.4426
gov_report_test	0.9869	0.9750	0.9832	0.9837	0.9816	0.9823	0.9855	0.9883	0.9853
legal_case_reports_test	0.3702	0.4476	0.5398	0.5432	0.5319	0.4850	0.5474	0.5875	0.6534
multifieldqa_test	0.9373	0.9341	0.9345	0.9327	0.9450	0.9321	0.9687	0.9564	0.9754
passage_retrieval_test	0.4493	0.5271	0.3470	0.3407	0.2902	0.3248	0.7562	0.7389	0.8550
qasper_abstract_test	1.0000	0.9806	0.9982	0.9982	0.9973	0.9965	0.9973	0.9982	0.9982
qasper_title_test	0.9860	0.8892	0.9838	0.9833	0.9861	0.9812	0.9742	0.9742	0.9840
qmsum_test	0.6668	0.6307	0.6816	0.7237	0.7169	0.7148	0.7438	0.7613	0.8154
stackoverflow_test	0.9634	0.9087	0.9760	0.9760	0.9766	0.9690	0.9362	0.9369	0.9443
summ_screen_fd_test	0.9320	0.9379	0.9747	0.9635	0.9656	0.9580	0.9796	0.9821	0.9788
Average	0.7168	0.7150	0.7525	0.7579	0.7517	0.7455	0.7886	0.7949	0.8406

Table 3: LoCoV1 ndcg@10 results

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