KaLM-Embedding-V2: Superior Training Techniques and Data Inspire A Versatile Embedding Model

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Superior Training Techniques and High-quality Data

Focal-style Reweighting Mechanism

- It emphasizes difficult samples, where the more difficult the sample, the larger the weight.

$$w_i = (1 - \frac{e^{s(\mathbf{q}_i,\mathbf{p}_i^+)/\tau}}{Z_i})^\gamma, \quad \mathcal{L} = \mathop{\mathbb{E}}_{i\in N}\left[-w_i \log \frac{e^{s(\mathbf{q}_i,\mathbf{p}_i^+)/\tau}}{Z_i}\right]$$

Online Hard Negative Mixing Strategy

- It synthesizes new informative hard negatives via pair-wise or list-wise mixing.

$$\mathbf{h}_i^- = \frac{\tilde{\mathbf{h}}_i^-}{\|\tilde{\mathbf{h}}_i^-\|_2}, \quad \tilde{\mathbf{h}}_i^- = \lambda \mathbf{p}_{i,j}^- + (1-\lambda)\mathbf{p}_{i,k}^-, \quad j \neq k, \quad j,k \in [1,M]$$

$$\mathbf{s}_i^- = \frac{\tilde{\mathbf{s}}_i^-}{\|\tilde{\mathbf{s}}_i^-\|_2}, \quad \tilde{\mathbf{s}}_i^- = \sum_{m=1}^{M} \lambda_m \mathbf{p}_{i,m}^-, \quad \text{s.t.} \sum_{m=1}^{M} \lambda_m = 1,$$

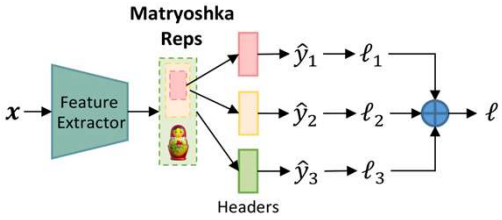
Contrastive Distillation

- It distills fine-grained soft signals from the teacher model that capture nuanced differences.

$$\mathcal{L}_{KL} = D_{KL}(P_t \| P_s) = \sum_i P_t(i) \log \frac{P_t(i)}{P_s(i)}, \quad P_t(i) = \frac{e^{z_{t,i}/\tau}}{\sum_j e^{z_{t,j}/\tau}}, \quad P_s(i) = \frac{e^{z_{s,i}/\tau}}{\sum_j e^{z_{s,j}/\tau}}$$

Matryoshka Representation Learning

- It enables flexible-dimensional embeddings.



Comprehensive Data Curation Recipe

- Around 20 categories of weakly supervised data as well as 100 categories of supervised data
- Hard Negative Mining
- Task-specific instructions
- Persona-based Data Synthesis
- Example-based multi-class labeling

Lychee-KaLM-Embedding-Data

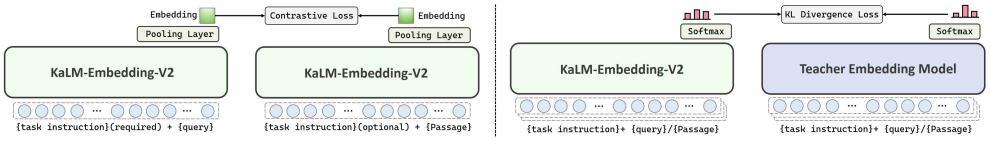
KaLM-Embedding/KaLM-embedding-finetuning-data
Viewer · Updated Nov 27, 2025 · 6.34M · 852 · 25

HIT-TMG/KaLM-embedding-pretrain-data
Viewer · Updated Nov 27, 2025 · 23.7M · 1.82k · 21

Training Framework and Recipe

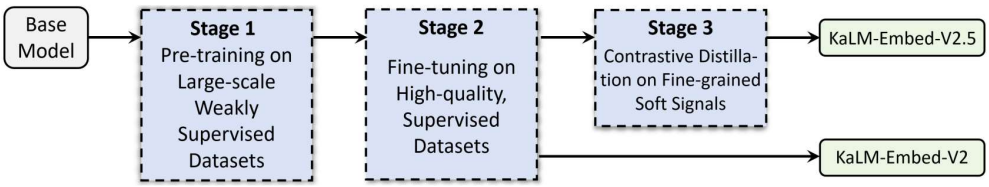
Overall Training Framework

- The left illustrates the workflow of contrastive learning, while the right shows that of contrastive distillation.



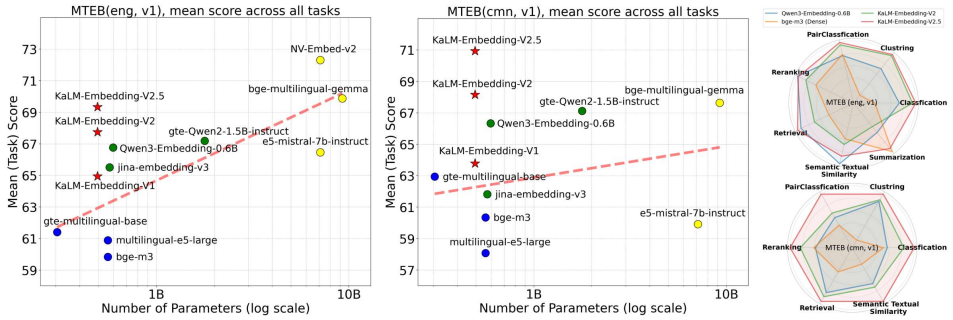
Progressive Multi-stage Training Recipe

- Pre-training on large-scale, weakly supervised datasets over 20 categories to endow the model with strong generalization.
- Fine-tuning on over 100 categories of high-quality supervised datasets to further improve the overall model performance.
- Contrastive Distillation with fine-grained soft knowledge from a stronger teacher model to capture nuanced semantic differences.

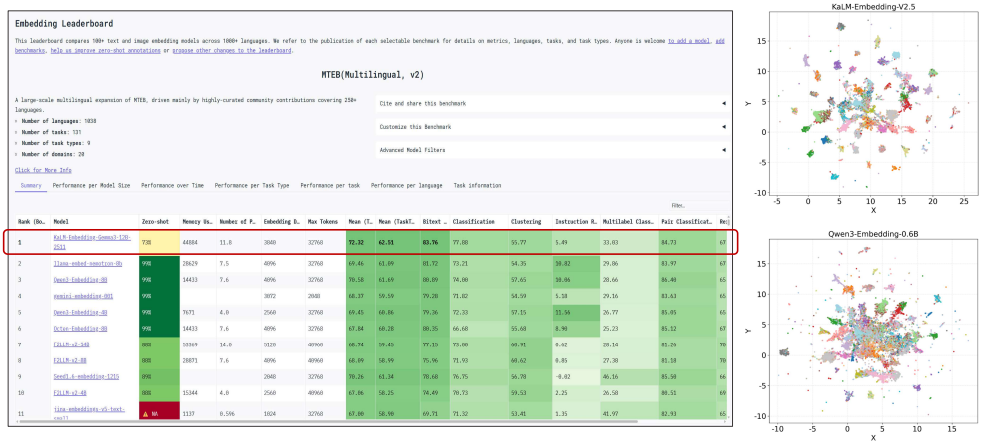


Experimental Results

- Our KaLM-Embedding-V2 series significantly outperforms models of comparable size, rivaling models 3–26x larger.



- KaLM-Embed-Gemma3 further advances SOTA on MMEB. KaLM-Embed-V2.5 shows superior intra-class compactness and inter-class separability.



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If you are interested in our work, please contact us!

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