viPolyQwen: Synergizing Prefix-Guided Dynamic Loss Optimization and Attention Pooling for Unified Multimodal Embeddings

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Abstract

(This paper is Architecture & Hypothesis. Training is still ongoing. Empirical Validation Required.)

Multimodal representation learning strives to bridge the semantic gap between disparate data types like text and images. While Vision-Language Models (VLMs) have advanced this frontier, generating unified embeddings that are both versatile across diverse tasks (similarity, retrieval, QA) and computationally efficient remains a significant challenge. Existing paradigms often resort to task-specific models, separate embedding spaces, or complex multi-vector architectures, potentially increasing system complexity and latency. We propose `viPolyQwen`, an approach for learning a single, high-dimensional (1024-d), unified multimodal embedding space $\mathcal{E}$. Building upon the Qwen2-VL-2B-Instruct foundation model, our proposed methodology combines: (1) a heterogeneous dataset ($\mathcal{D}$, $|\mathcal{D}| > 11 \times 10^6$) encompassing five distinct multimodal interaction types (text similarity, instruction following, OCR, single/multi-turn VQA), with emphasis on Vietnamese alongside multilingual data; (2) a **prefix-guided dynamic mixed-loss optimization strategy** that conditions the learning process, tailoring the objective function ($\mathcal{L}_{\text{NCE}}$, $\mathcal{L}_{\text{Triplet}}$, $\mathcal{L}_{\text{MSE}}$, $\mathcal{L}_{\text{Cos}}$) on a per-sample basis during training via discrete task prefixes p_i; and (3) an **Attention Pooling** mechanism that aggregates information from the VLM encoder's output sequence $\mathbf{H}$, weighting features based on learned importance (α_i weights for $\mathbf{h}_i$). We hypothesize that this synergistic approach may yield an architecturally simpler embedding model while potentially outperforming standard pooling baselines. As empirical validation is currently in progress, we present this work to stimulate discussion on unified multimodal embeddings, particularly for applications involving complex, text-rich visual inputs.

1. Introduction

The proliferation of multimodal information necessitates AI systems capable of understanding and reasoning across text, vision, and structured data. A cornerstone of such systems is the ability to represent diverse inputs within a shared vector space $\mathcal{E} \subset \mathbb{R}^{D_{\text{embed}}}$, enabling semantic search, cross-modal retrieval, and Retrieval-Augmented Generation (RAG) [1]. While Vision-Language Models (VLMs) [2, 3, 4] have demonstrated promising capabilities in aligning vision and language, translating their internal representations into effective, general-purpose embeddings presents several challenges.

Firstly, fine-tuning VLMs typically yields embeddings specialized for a single task objective $\mathcal{L}_{\text{task}}$ (e.g., image-text contrastive loss in CLIP [2]). While effective for that specific task, these embeddings may be suboptimal for others with different geometric requirements in $\mathcal{E}$ (e.g., fine-grained text similarity regression or visual question answering grounding) within the *same* embedding space. This can necessitate maintaining multiple specialized models, increasing operational complexity.

Secondly, representing complex, structured inputs like documents often leads to multi-vector approaches [5, 6]. These methods decompose the input into multiple representations (e.g., global context $\mathbf{e}_{\text{global}}$, local patches $\{\mathbf{e}_{\text{local},i}\}$). While potentially capturing finer granularity, they introduce significant downstream complexity, requiring specialized indexing structures and multi-stage retrieval algorithms (e.g., ColBERT-style late interaction [7]) that deviate from standard, highly optimized dense vector search paradigms (like FAISS [8]).

Thirdly, the mechanism used to pool the sequence of VLM encoder outputs $\mathbf{H} \in \mathbb{R}^{N \times D_{\text{hidden}}}$ into a single vector $\mathbf{c} \in \mathbb{R}^{D_{\text{hidden}}}$ significantly impacts the final embedding quality. Standard strategies like mean pooling ($\mathbf{c}_{\text{mean}} = \frac{1}{N}\sum \mathbf{h}_i$) may dilute salient information, while last-token pooling ($\mathbf{c}_{\text{last}} = \mathbf{h}_N$) may overlook potentially

important context from earlier in the sequence. This could be particularly limiting for information-dense inputs like documents or images containing embedded text.

To address these challenges, we propose `viPolyQwen`, a unified multimodal embedding model built upon Qwen2-VL-2B-Instruct [3]. Our approach seeks to generate a single 1024-dimensional vector $\mathbf{e} \in \mathbb{R}^{1024}$ capable of representing diverse multimodal inputs effectively. Its design is guided by three core principles:

1. **Highly Diverse Multi-Task Training Data:** We curate a large-scale dataset ($D = \{(x_i, y_i, \text{type}_i, ...)\}_{i=1}^{M}$, $M > 11 \times 10^6$) incorporating five distinct data formats (`type`) and associated tasks: text similarity pairs (with scores s_i), instruction-following sequences, Optical Character Recognition (OCR) / Optical Character Questioning (OCQ), single-turn Visual Question Answering (VQA), and multi-turn VQA. This diversity, with a focus on Vietnamese and substantial multilingual components, aims to foster robustness and generalization.
2. **Prefix-Guided Dynamic Loss Optimization:** We propose an explicit conditioning mechanism during training. Task-specific prefixes $p_i \in P = \{\texttt{<ocr>}, \texttt{<text\_pair>}, \texttt{<instr>}, \texttt{<vqa\_single>}, \texttt{<vqa\_multi>}\}$ are prepended to the input x_i. This prefix p_i serves as a discrete signal that dynamically selects a tailored objective function $\mathcal{L}_{\text{type}(p_i)}$ (composed of InfoNCE, Triplet Margin, MSE, Cosine Similarity components) specifically optimized for that task structure. This may allow the model, represented by parameters θ, to learn task-aware representations within the unified space $\mathcal{E}$.
3. **Attention Pooling for Richer Embeddings:** Departing from standard pooling, we implement a learnable Attention Pooling mechanism (Section 3.2) over the final hidden state sequence $\mathbf{H}$. This is designed to enable the model to identify and weight features based on learned importance (α_i weights for $\mathbf{h}_i$), potentially producing a more contextually relevant intermediate representation $\mathbf{c} = \sum \alpha_i \mathbf{h}_i$ before projection to the final embedding $\mathbf{e}$.

We hypothesize and aim to validate through ongoing work that the combination of diverse multi-task learning, prefix-guided dynamic loss adaptation, and attention-based feature aggregation might enable `viPolyQwen` to produce unified 1D embeddings that balance performance with architectural simplicity. This work has been conducted in collaboration with the AI technology team at Gtel Mobile JSC (GMobile), whose support has been valuable in this research endeavor.

2. Related Work

Our work builds upon and relates to several research directions:

- **Multimodal Contrastive Learning (e.g., CLIP, ALIGN):** Foundational models like CLIP [2] and ALIGN [9] have demonstrated effective image-text alignment through contrastive learning across large datasets. However, a single contrastive objective, while effective for retrieval, may not optimally capture the nuances required for diverse downstream tasks like fine-grained semantic similarity regression or structured QA grounding within the *same* embedding space. Adapting these models often requires further task-specific fine-tuning, potentially leading to multiple specialized models or compromising the original general alignment. The proposed `viPolyQwen` approach attempts to address this by incorporating multiple loss formulations within a single training framework, guided by task type.
- **Sentence & Text Embeddings (e.g., Sentence-BERT):** Fine-tuning approaches like Sentence-BERT [10] typically focus on optimizing for a specific pair-based task structure (e.g., semantic similarity using NLI data or regression on STS benchmarks). Applying such a focused approach naively to multimodal, multi-task data might create embeddings biased towards one structure, potentially affecting performance on other tasks. The dynamic loss selection mechanism in our proposed approach aims to apply appropriate optimization for each data type encountered.
- **Document AI & Multi-Vector Representations (e.g., ColPali):** Addressing the complexity of structured documents, multi-vector approaches like ColPali [5] dedicate separate representations for different granularities (e.g., global context + local patches). While potentially capturing fine-grained detail, this necessitates specialized retrieval mechanisms like ColBERT-style late interaction [7], which may deviate from standard, highly efficient vector search. Our prefix-guided approach, coupled with Attention Pooling, explores an alternative possibility: whether a *single* vector could effectively encode task-relevant nuances and salient features to handle diverse tasks, thereby maintaining architectural simplicity.
- **Pooling Mechanisms:** While mean/max/last-token pooling are computationally efficient, they may not optimally aggregate information. Self-attention pooling [11] can be more expressive but adds complexity.

Our Attention Pooling mechanism (Section 3.2) attempts to balance effectiveness and efficiency through a learnable context vector approach.

- **Multi-Task Learning & Dynamic Loss:** Training models on multiple tasks simultaneously can improve generalization [12]. Dynamically selecting or weighting losses may help navigate conflicting gradient signals [13, 14]. Our prefix-guided mechanism provides an *explicit, discrete* signal for selecting task-optimized loss combinations, potentially ensuring appropriate geometric constraints are applied during optimization for each sample type.
- **Vietnamese & Cross-Lingual Models:** Our work addresses the need for multimodal embeddings for Vietnamese, leveraging substantial native data alongside multilingual resources to potentially foster both in-language performance and cross-lingual capabilities [15].

The proposed contribution of `viPolyQwen` lies in the integration of: (1) a powerful VLM backbone, (2) conditioning the learning process on diverse task structures via prefix signals coupled with dynamic loss selection, and (3) employing Attention Pooling to generate a unified embedding. This approach seeks to address limitations of single-objective training, task-specific fine-tuning, and multi-vector representation architectures.

3. Methodology

3.1 Model Architecture

The `viPolyQwen` embedder builds upon the `Qwen/Qwen2-VL-2B-Instruct` model [3]. The core components involved in generating the final 1D embedding $\mathbf{e} \in \mathbb{R}^{1024}$ are:

1. **Qwen-VL Processor & Encoder:** Inputs (text, images) are processed and tokenized by the `AutoProcessor`. During training, textual inputs are augmented with task prefixes p_i (Section 3.4). The multimodal encoder processes these inputs, yielding a sequence of final layer hidden states:

$$\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, ..., \mathbf{h}_N] \in \mathbb{R}^{N \times D_{\text{hidden}}}$$

   where $\mathbf{h}_i$ represents the contextualized state for the i-th token or visual patch, and D_{hidden} is the hidden dimension of the base VLM (e.g., 2048 for Qwen2-VL-2B).

2. **Attention Pooling Layer:** This layer (Section 3.2) aggregates the hidden state sequence $\mathbf{H}$ into a single context vector $\mathbf{c} \in \mathbb{R}^{D_{\text{hidden}}}$.

3. **Enhanced Multi-Layer Projection Head:** A sophisticated trainable projection head transforms the pooled context vector $\mathbf{c}$ into the target embedding space through a series of transformations:

$$\mathbf{p} = \text{LayerNorm}(\mathbf{W}_{\text{proj2}} \cdot \text{GELU}(\text{LayerNorm}(\mathbf{W}_{\text{proj1}}\mathbf{c})))$$

   where:

   - $\mathbf{W}_{\text{proj1}} \in \mathbb{R}^{D_{\text{embed}} \times D_{\text{hidden}}}$ is the first linear transformation
   - GELU introduces non-linearity to enhance feature expressivity
   - The intermediate layer normalization stabilizes training dynamics
   - $\mathbf{W}_{\text{proj2}} \in \mathbb{R}^{D_{\text{embed}} \times D_{\text{embed}}}$ is the second linear projection
   - The final layer normalization ensures consistent feature scales

   This enhanced projection architecture with intermediate activations and multiple normalization layers is designed to better preserve semantic information during dimensionality reduction, potentially allowing for more nuanced representation of multimodal concepts.

4. **L2 Normalization:** The final embedding $\mathbf{e} \in \mathbb{R}^{D_{\text{embed}}}$ is obtained by L2 normalizing the projected vector $\mathbf{p}$:

$$\mathbf{e} = \frac{\mathbf{p}}{||\mathbf{p}||_2}$$

   This ensures all embeddings reside on the unit hypersphere, facilitating cosine similarity comparisons.

3.2 Attention Pooling Mechanism

To derive the context vector $\mathbf{c}$ from the hidden state sequence $\mathbf{H}$, we implement Attention Pooling. Unlike mean pooling ($\mathbf{c} = \frac{1}{\sum M_j} \sum_i M_i \mathbf{h}_i$) or last-token pooling ($\mathbf{c} = \mathbf{h}_{\sum M_j}$), Attention Pooling computes a weighted average where weights reflect the learned importance of each hidden state.

1. **Learnable Context Vector:** We introduce a trainable parameter vector $\mathbf{v}_a \in \mathbb{R}^{D_{\text{hidden}}}$ (denoted `attention_context_vector`), initialized randomly (e.g., $\mathcal{N}(0, 0.02^2)$) and updated during training. This vector is designed to function as a learnable "query" representing the concept of "salience" within the sequence context.
2. **Attention Scores:** An unnormalized attention score u_i is computed for each hidden state $\mathbf{h}_i$ via dot product:

$$u_i = \mathbf{h}_i^T \mathbf{v}_a$$

3. **Masking:** Scores corresponding to padded positions (identified via the attention mask $\mathbf{M} \in \{0, 1\}^N$) are masked:

$$u'_i = \begin{cases} u_i & \text{if } M_i = 1 \\ -\infty & \text{if } M_i = 0 \end{cases}$$

4. **Attention Weights:** The masked scores are normalized using softmax:

$$\alpha_i = \frac{\exp(u'_i)}{\sum_{j=1}^{N} \exp(u'_j)}$$

5. **Weighted Average:** The final pooled context vector $\mathbf{c}$ is computed:

$$\mathbf{c} = \sum_{i=1}^{N} \alpha_i \mathbf{h}_i$$

This mechanism is designed to allow the model to focus on potentially informative parts of the sequence (e.g., keywords, salient visual regions, text-in-image) when constructing the 1D representation.

3.3 Enhanced Multi-Layer Projection Head

The projection head has been significantly enhanced from a simple linear transformation to a multi-layer architecture that introduces non-linearity and additional normalization. This design choice is motivated by several theoretical and practical considerations:

1. **Expressive Power**: The introduction of the GELU non-linearity between linear transformations enables the projection head to learn more complex transformations from the high-dimensional hidden space to the embedding space, potentially capturing intricate semantic relationships that a linear projection might miss.
2. **Feature Disentanglement**: Multiple layers with non-linearities can help disentangle features in the representation space, separating task-specific information from modality-specific information, thereby enhancing the unified nature of the resulting embeddings.
3. **Gradient Flow**: The intermediate layer normalization helps stabilize gradient flow during training, potentially addressing challenges with optimizing representations across diverse loss functions and task types.
4. **Representation Preservation**: The sophisticated architecture may better preserve important semantic information during dimensionality reduction from D_{hidden} (2048) to D_{embed} (1024).

Formally, the projection head implements the following transformations:

1. First linear transformation: $\mathbf{z}_1 = \mathbf{W}_{\text{proj1}} \mathbf{c}$
2. First layer normalization: $\mathbf{z}_2 = \text{LayerNorm}(\mathbf{z}_1)$

3. GELU activation: $\mathbf{z}_3 = \text{GELU}(\mathbf{z}_2)$
4. Second linear transformation: $\mathbf{z}_4 = \mathbf{W}_{\text{proj2}}\mathbf{z}_3$
5. Final layer normalization: $\mathbf{p} = \text{LayerNorm}(\mathbf{z}_4)$

This multi-layer projection architecture represents a significant enhancement over simpler projection approaches used in many prior embedding models, potentially allowing for more powerful and nuanced unified representations across our diverse multimodal tasks.

3.4 Prefix-Guided Input Representation & Conditioning (Training)

During training, the `MixedBatchCollator` preprocesses each sample $(x_i, y_i, \text{type}_i, ...)$. Based on `data_type`, a prefix $p_i \in P = \{\texttt{<ocr>}, ..., \texttt{<vqa\_multi>}\}$ is prepended to the textual input x_i, yielding $x'_i = (\text{prefix}(p_i), x_i)$.

This explicit prefix p_i acts as a **conditioning signal**. Let the embedding function be $f_\theta : (X', P) \mapsto \mathcal{E}$. The prefix p_i directly influences the selection of the loss function $\mathcal{L}_{\text{type}(p_i)}$ (Section 4.2). The gradient contributing to the update of shared parameters θ is thus task-dependent:

$$\nabla_\theta \mathcal{L}_{\text{batch}} = \frac{1}{B} \sum_{i=1}^{B} \nabla_\theta \mathcal{L}_{\text{type}(p_i)}(f_\theta(x'_i), f_\theta(y'_i))$$

This explicit conditioning is hypothesized to enable task specialization *within* the unified space $\mathcal{E}$. For inference on general data, no prefix is used ($p = \text{None}$), yielding a general-purpose embedding $f_\theta(x, \text{None})$.

3.4.1 Theoretical Foundations for Prefix-Guided Conditioning

The necessity of prefix tokens in the viPolyQwen architecture emerges from fundamental challenges in creating unified multimodal embedding spaces. We identify and address three core theoretical issues that motivate our approach:

Task Ambiguity and Input Space Entanglement

For heterogeneous multimodal data types that share structural similarities, the model may face inherent ambiguity in determining the appropriate embedding strategy. Formally, we can express this as an input classification problem $\mathcal{C} : \mathcal{X} \to \mathcal{T}$ that maps inputs to their appropriate task types, where $\mathcal{T} = \{\text{text\_pair}, \text{ocr}, \text{instr}, \text{vqa\_single}, \text{vqa\_multi}\}$. Without explicit signals, the function $\mathcal{C}$ becomes ill-defined due to overlapping input distributions:

$$P(\mathcal{X}_{\text{ocr}}) \cap P(\mathcal{X}_{\text{vqa\_single}}) \neq \emptyset$$
$$P(\mathcal{X}_{\text{text\_pair}}) \cap P(\mathcal{X}_{\text{instr}}) \neq \emptyset$$

For instance, an image with text and a question could represent either an OCR task (requiring precise text localization) or a visual question-answering task (requiring broader scene understanding). Without additional signaling, the model must implicitly infer task type, potentially introducing noise into the learning process. Prefix tokens provide an explicit, unambiguous signal p_i that resolves this classification uncertainty, formally:

$$P(\mathcal{T} = t | \mathcal{X} = x, P = p_t) = 1$$

where p_t is the task-specific prefix for task $t \in \mathcal{T}$.

Conflicting Geometric Constraints in Embedding Space

Each task-specific loss function imposes distinct geometric constraints on the embedding space $\mathcal{E}$. We can formalize these constraints as manifolds or regions within $\mathcal{E}$ where:

- For InfoNCE loss ($\mathcal{L}_{\text{NCE}}$): Positive pairs should be closer than all negatives by a certain margin in a batch-dependent context.
- For Triplet Margin loss ($\mathcal{L}_{\text{Triplet}}$): Positive pairs should maintain a fixed minimum distance from the hardest negative.
- For MSE Similarity Regression ($\mathcal{L}_{\text{MSE}}$): Embedding similarity should match a continuous target score, creating a regression manifold.
- For Cosine Similarity Maximization ($\mathcal{L}_{\text{Cos}}$): Directly maximizes alignment between specific pairs.

These constraints can conflict when applied simultaneously to inputs from different tasks but with similar structure. Formally, we can express the optimal embedding regions for different losses as:

$$\mathcal{E}_{\text{optimal}}^{\mathcal{L}_{\text{NCE}}} \cap \mathcal{E}_{\text{optimal}}^{\mathcal{L}_{\text{MSE}}} \neq \mathcal{E}_{\text{optimal}}^{\mathcal{L}_{\text{NCE}}} \text{ and } \neq \mathcal{E}_{\text{optimal}}^{\mathcal{L}_{\text{MSE}}}$$

Our prefix-guided approach addresses this by providing task context that supports "multimodal loss disambiguation":

$$\nabla_\theta \mathcal{L}(f_\theta(x_i'), f_\theta(y_i')) = \nabla_\theta \mathcal{L}_{\text{type}(p_i)}(f_\theta(x_i'), f_\theta(y_i'))$$

This allows the model to navigate the trade-offs between competing geometric constraints in a principled manner, activating appropriate optimization pressures for each sample based on its task characteristics.

Neuron Activation Specialization and Knowledge Transfer

Prefix tokens enable what we term "conditional activation patterns" within the model's parameters. With a conditional input p_i, certain neurons or attention heads may specialize in task-specific features while maintaining shared representations, formally:

$$\mathbf{h}_j^{(l)} = \sigma\left(\mathbf{W}_j^{(l)}\mathbf{h}^{(l-1)} + \mathbf{b}_j^{(l)}\right) \cdot g(p_i, \mathbf{h}^{(l-1)})$$

where $g(p_i, \mathbf{h}^{(l-1)})$ represents a modulation function influenced by the prefix token. For example, when processing an OCR sample (prefix `<ocr>`), neurons specialized in text localization may exhibit higher activation levels, while for VQA samples, neurons attuned to semantic relationships might dominate.

This controlled form of specialization offers two key benefits:

1. **Parameter Efficiency**: Rather than training entirely separate models for each task, parameters are shared with targeted conditional activations.
2. **Cross-Task Knowledge Transfer**: Learning from one task implicitly benefits others through shared parameters, while task-specific aspects remain differentiated via the prefix conditioning signal.

The interplay between Attention Pooling and prefix-guided conditioning creates a synergistic effect: Attention Pooling focuses on extracting contextually important features from the sequence, while prefix tokens guide which features should be considered important in the current task context.

3.4.2 Prefix Usage in Training vs. Inference

A distinguishing aspect of our approach is the asymmetry between training and inference prefix usage:

- **During Training**: Every input explicitly includes a task-specific prefix to guide loss selection and facilitate task-aware representation learning.
- **During Inference (General Case)**: For most common embedding scenarios (text chunks, single images, image+caption), no prefix is required. The model learns to produce generalized embeddings that capture unified multimodal understanding.
- **During Inference (Specialized Case)**: For specific task scenarios like OCR querying or focused VQA retrieval, prefixes can optionally be included to "steer" the embedding toward task-optimized regions of the embedding space.

This design offers a unique compromise: encoding task-specialized knowledge during training while providing simplified, prefix-free inference for general use cases. When fine-grained control or specialized capabilities are needed, prefixes can be selectively reintroduced at inference time.

The general-purpose embedding function without prefixes is defined as:

$$\mathbf{e}_{\text{general}}(x) = f_\theta(x, \text{None})$$

While the task-steered embedding function with prefixes is:

$$\mathbf{e}_{\text{task}}(x, t) = f_\theta(x, p_t)$$

This dual interface balances simplicity for common use cases with the power of task-specific optimization when required.

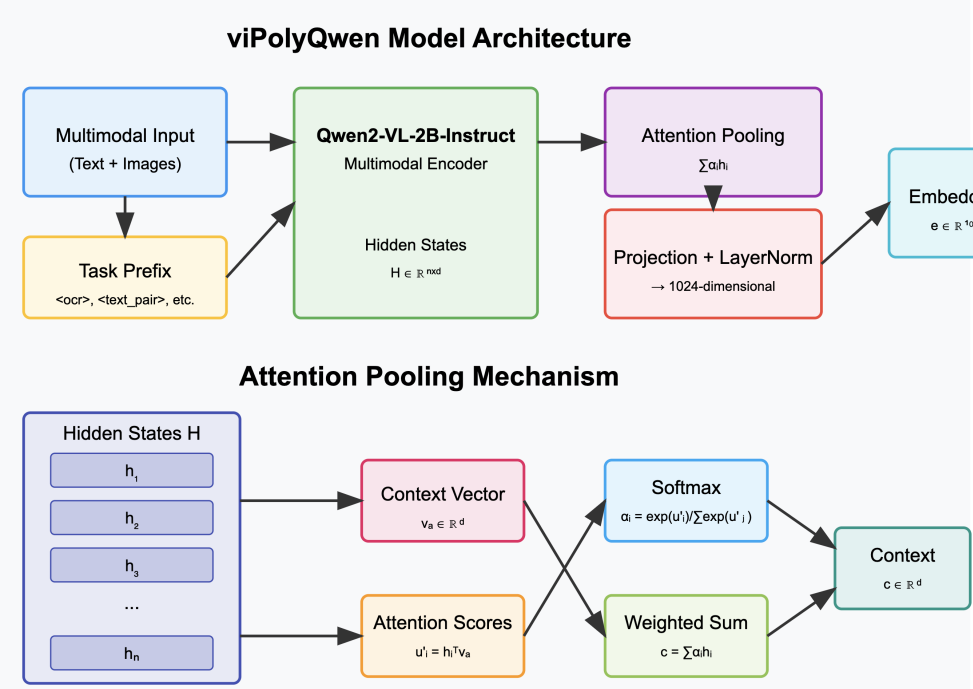

Figure 1: viPolyQwen Architecture

4. Training Paradigm

4.1 Dataset Composition

The model is trained on a composite dataset $\mathcal{D}$ (>11M samples) covering:

- **Text Similarity (`<text_pair>`):** Text pairs (x_i, y_i) with similarity scores s_i. (Vi/En/Zh)
- **Instruction Following (`<instr>`):** (Instruction, Output) pairs (x_i, y_i).
- **OCR/OCQ (`<ocr>`):** (Image(s)+Question, Answer) triples (x_i, y_i).
- **Single/Multi-turn VQA (`<vqa_...>`)**: (Image(s)+Context/Question, Answer) triples (x_i, y_i).

The dataset comprises predominantly Vietnamese (approximately 60%), with English (approximately 30%) and Chinese (approximately 10%) portions.

4.2 Prefix-Guided Dynamic Mixed-Loss Optimization

The training objective dynamically applies task-specific losses based on prefix p_i. Let $(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}) = (f_\theta(x'_i), f_\theta(y'_i))$ be normalized embeddings.

- **For p_i = `<text_pair>`:** Combines contrastive loss and score regression.

$$\mathcal{L}_{\text{text\_pair}} = \lambda_{\text{nce}}\mathcal{L}_{\text{NCE}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}, \mathcal{B}, T) + \lambda_{\text{mse}}\mathcal{L}_{\text{MSE}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}, s_i)$$

where $T = 0.07$, $\lambda_{\text{nce}} = \lambda_{\text{mse}} = 1.0$, $\mathcal{L}_{\text{MSE}} = (\frac{1}{2}(\mathbf{e}_{a,i}^T\mathbf{e}_{b,i} + 1) - s_i)^2$, and $\mathcal{L}_{\text{NCE}}$ is symmetric InfoNCE over batch $\mathcal{B}$:

$$\mathcal{L}_{\text{NCE}} = -\frac{1}{2B}\sum_{k=1}^{B}\left[\log\frac{\exp(S_{k,k}/T)}{\sum_{j=1}^{B}\exp(S_{k,j}/T)} + \log\frac{\exp(S_{k,k}/T)}{\sum_{j=1}^{B}\exp(S_{j,k}/T)}\right]$$

with $S_{kj} = \mathbf{e}_{a,k}^T\mathbf{e}_{b,j}$.

- **For $p_i =$ `<instr>`:** Combines contrastive loss and direct similarity maximization.

$$\mathcal{L}_{\text{instr}} = \lambda_{\text{nce}}\mathcal{L}_{\text{NCE}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}, \mathcal{B}, T) + \lambda_{\text{cos}}\mathcal{L}_{\text{Cos}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i})$$

where $\lambda_{\text{cos}} = 1.0$ and $\mathcal{L}_{\text{Cos}} = (1 - \mathbf{e}_{a,i}^T\mathbf{e}_{b,i})$.

- **For $p_i \in \{$`<ocr>`, `<vqa_...>`$\}$:** Combines contrastive loss and triplet margin loss.

$$\mathcal{L}_{\text{ocr/vqa}} = \lambda_{\text{nce}}\mathcal{L}_{\text{NCE}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}, \mathcal{B}, T) + \lambda_{\text{trip}}\mathcal{L}_{\text{Triplet}}(\mathbf{e}_{a,i}, \mathbf{e}_{b,i}, \mathcal{N}_i, m', T)$$

where $\lambda_{\text{trip}} = 1.0$ (or 1.5 for multi-turn), $m' = 0.2$ (or 0.3 for multi-turn), $\mathcal{N}_i = \{\mathbf{e}_{b,j} \mid j \neq i\}$, and

$$\mathcal{L}_{\text{Triplet}} = \max\left(0, \max_{\mathbf{e}_n \in \mathcal{N}_i}\frac{\mathbf{e}_{a,i}^T\mathbf{e}_n}{T} - \frac{\mathbf{e}_{a,i}^T\mathbf{e}_{b,i}}{T} + m'\right)$$

The overall batch loss is $\mathcal{L}_{\text{batch}} = \frac{1}{B}\sum_{i=1}^{B}\mathcal{L}_{\text{type}(p_i)}$.

4.3 Implementation Details (ongoing):

- **Hardware:** 4x NVIDIA H100 GPUs (94GB VRAM).
- **Framework:** Hugging Face `accelerate` with FSDP ZeRO-3.
- **Precision:** `bfloat16` mixed precision, Flash Attention 2.
- **Optimizer:** AdamW [17].
- **Learning Rate:** 1×2^{-5} initial 15% warmup, with subsequent cosine decay
- **Batch Size:** Per-device 16, gradient accumulation 4 (Global: 256).
- **Sequence Length:** 12288 tokens.
- **Training Duration:** 2 epochs (approximately 15 days).
- **Regularization:** Weight decay 0.1, max gradient norm 3.0.
- **Loss Parameters:** $T = 0.07$, $m = 0.2$ (base). λ's $= 1.0$.
- **Tokenizer:** Extended Qwen-VL tokenizer with new prefix tokens and embedding model's layer resized.

4.4 Complementary Roles of Attention Pooling and Enhanced Projection Head

While both Attention Pooling and the enhanced projection head contribute to improved representations, they serve distinct but complementary functional roles within the model architecture:

Attention Pooling focuses on the problem of information extraction from the encoder's output sequence. It addresses the question: "How do we best summarize the sequence of hidden states into a single vector?" By learning to assign attention weights α_i to each token/patch representation $\mathbf{h}_i$, it creates a nuanced weighted average that emphasizes the most salient features for the final embedding.

The **Enhanced Multi-Layer Projection Head** addresses a different concern: "How do we best transform the pooled representation into an embedding that preserves semantic structure while reducing dimensionality?" The sophisticated projection architecture with non-linearities and multiple normalization layers creates a more expressive mapping function that can potentially:

1. Disentangle correlated features from the VLM's hidden states
2. Accentuate task-relevant information while suppressing noise
3. Structure the final embedding space to better accommodate the conflicting geometric constraints imposed by different loss functions

The relationship between these mechanisms produces a cascade of information refinement:

1. **Attention Pooling** transforms the encoder hidden states into a context vector by identifying important tokens/patches:

$$\mathbf{c} = \sum_{i=1}^{N} \alpha_i \mathbf{h}_i$$

2. **Enhanced Projection Head** further refines this vector through a series of non-linear transformations:

$$\mathbf{p} = \text{LayerNorm}(\mathbf{W}_{\text{proj2}} \cdot \text{GELU}(\text{LayerNorm}(\mathbf{W}_{\text{proj1}}\mathbf{c})))$$

3. **Prefix-Guided Conditioning** influences which loss function is applied to this projected vector:

$$\mathcal{L} = \mathcal{L}_{\text{type}(p_i)}(f_\theta(x_i'), f_\theta(y_i'))$$

This complementary design enables a form of "multi-level adaptation" - Attention Pooling adapts the feature extraction process, the enhanced projection head adapts the feature transformation process, and prefix conditioning adapts the optimization process - all working together to create a unified embedding space capable of representing diverse multimodal inputs.

5. Experimental Design and Evaluation Plan

As `viPolyQwen` is currently undergoing training, we outline a comprehensive evaluation plan designed to assess its capabilities and validate our core hypotheses upon completion.

5.1 Target Benchmarks and Metrics

Our evaluation strategy encompasses standard cross-modal benchmarks, tasks specific to Vietnamese, and assessments relevant to document understanding:

- **Image-Text Retrieval (Zero-Shot):** Evaluation on established datasets like MS-COCO 5k Captions [18] and Flickr30k [19]. Standard metrics including Recall@K (R@1, R@5, R@10) and Mean Rank (MeanR) will be computed for both Text-to-Image (T->I) and Image-to-Text (I->T) directions.
- **Vietnamese Semantic Textual Similarity (STS):** Performance will be measured on the ViSTS subset of the ViTextEval suite [20], using Spearman's rank correlation coefficient (ρ) between the cosine similarity of generated embeddings and human judgments.
- **Document Context Retrieval (Proxy for Document VQA):** Using datasets like DocVQA [21], we will assess the ability of embeddings to retrieve document pages containing answers to visual questions. Metrics will include Page Retrieval Accuracy@K (Acc@1, Acc@5), serving as a proxy for the embedding's utility in supporting document understanding tasks.
- **Ablation Studies:** A held-out internal validation set (5k samples) will be used to quantify the individual contributions of key components (Attention Pooling vs. Mean Pooling; Dynamic Loss vs. Single Objective; Enhanced Projection vs. Simple Projection).

5.2 Baselines for Comparison

To contextualize the performance of our approach, we plan to compare against several relevant baselines:

- **Strong Image-Text Models:** CLIP (ViT-L/14) [2] as a foundational contrastive learning baseline.
- **Base VLM (Simplified Pooling):** The Qwen2-VL-2B-Instruct model [3] with standard mean pooling applied to its final hidden states, projected to the same 1024-d dimension, serving as a direct architectural baseline.
- **Multilingual Models:** Representative multilingual text-image models (e.g., mCLIP adaptations [22]) for cross-lingual STS evaluation.
- **Ablation Variants:**
  - `viPolyQwen-MeanPool`: Our model trained with the full prefix-guided dynamic loss suite but utilizing mean pooling instead of Attention Pooling.
  - `viPolyQwen-NCEOnly`: Our model trained with Attention Pooling but employing only the InfoNCE loss component for all data types.

  - `viPolyQwen-SimpleProj`: Our model with the simplified projection head (single linear layer + layer norm) instead of the enhanced multi-layer architecture.
- **Conceptual Comparison:** We will qualitatively discuss architectural trade-offs and potential performance implications relative to multi-vector paradigms like ColPali [5], particularly concerning system complexity and deployment efficiency.

5.3 Evaluating the Specific Contributions of Prefix-Guided Conditioning and Enhanced Projection

To rigorously assess the impact of our proposed architecture components, we will include additional experimental analyses:

- **Implicit Task Inference vs. Prefix Conditioning**: A model variant trained without explicit prefixes that must infer task type from input structure alone, compared against our prefix-guided approach.
- **Simple vs. Enhanced Projection Head**: Comparative analysis of the same model architecture with simple linear projection versus our enhanced multi-layer projection across all benchmark tasks, to isolate the contribution of the projection head's expressivity.
- **Fixed Loss Weighting vs. Dynamic Selection**: A model using the same loss combination (weighted sum of all loss components) for all samples, regardless of task type, compared against our dynamic task-specific loss selection approach.
- **Prefix Ablation by Task**: Selective removal of specific prefixes to measure their impact on corresponding task performance.

For each variant, we will evaluate both task-specific performance (e.g., OCR accuracy, similarity regression) and cross-task generalization to quantify how each architectural component contributes to the model's unified multimodal capabilities.

6. Research Hypotheses

This research explores several hypotheses regarding our proposed methodology. The ongoing training and subsequent evaluation are designed to examine these propositions. We present them to invite discussion from the research community:

1. **H1: On the Effectiveness of Attention Pooling for Unified Embeddings:** We hypothesize that the learnable Attention Pooling mechanism (Section 3.2) may capture more salient visual and textual information from the VLM encoder's output sequence compared to standard mean pooling. By dynamically weighting features based on learned importance, it might produce a more discriminative 1D embedding, particularly for information-dense inputs like documents containing text or complex visual scenes.
2. **H2: On Prefix-Guided Dynamic Loss and Task Versatility:** We propose that explicitly conditioning the training on task type via prefixes and applying tailored loss functions may be beneficial for achieving robust performance across the diverse tasks in our training data. A single contrastive objective might be suboptimal compared to the dynamic loss strategy, which applies task-specific geometric constraints within the unified embedding space.
3. **H3: On the Viability of Unified Single-Vector Representation:** We explore whether the combination of a powerful VLM foundation, diverse multi-task dynamic training, and Attention Pooling might enable encoding sufficient multimodal nuance within a single vector to be competitive with more complex architectures, while providing deployment advantages (standard indexing/search infrastructure, potentially lower latency).
4. **H4: On Multilingual and Vietnamese Performance:** Given the substantial proportion of Vietnamese data in our training set, we aim to investigate whether our approach can establish a viable baseline for Vietnamese multimodal embedding tasks, performing competitively with models specifically optimized for the language.
5. **H5: On the Necessity of Explicit Task Disambiguation:** We hypothesize that the explicit prefix-guided approach will outperform implicit task inference, particularly for structurally similar inputs with different semantic requirements (e.g., OCR vs. general VQA on text-containing images). This hypothesis addresses whether the benefits of explicit conditioning outweigh the simplicity of prefix-free training.
6. **H6: On Conflicting Geometric Constraints:** We propose that different task types inherently benefit from different loss functions due to their distinct geometric requirements in embedding space. The dynamic

loss selection mechanism should demonstrate measurable advantages over applying any single loss function across all tasks, or even over applying a fixed weighted combination of losses.

7. **H7: On the Impact of Enhanced Projection Architecture:** We hypothesize that the non-linear multi-layer projection head with intermediate normalization layers will outperform a simple linear projection, particularly for tasks requiring fine-grained semantic distinctions. The enhanced expressivity may better preserve key information during dimensionality reduction and help resolve conflicts between different task geometries in the shared embedding space.

Call for Discussion: As the training process for such a large-scale model requires significant resources, we present these hypotheses and our experimental design prior to obtaining final results to invite feedback from the community. We welcome suggestions for additional benchmarks, baselines, or insights regarding our proposed approach.

7. Conclusion and Future Directions

In this paper, we have introduced `viPolyQwen`, a framework for learning unified multimodal embeddings within a single vector space. The approach integrates three key components: a diverse multi-task training dataset, a prefix-guided mechanism for dynamically selecting task-optimized loss functions, and an Attention Pooling layer for feature aggregation, complemented by an enhanced multi-layer projection head. The central hypothesis is that this integration might yield embeddings that are versatile across different modalities and tasks while maintaining architectural simplicity.

The immediate next step is completing the ongoing training phase, followed by rigorous empirical validation through the evaluation plan outlined in Section 5. This will involve comparing our approach against established baselines and conducting ablation studies to understand the contribution of each component. Upon completion of this validation, we plan to release model checkpoints, evaluation code, and usage guidelines to facilitate further research.

Future Research Directions: Subject to empirical validation of our approach, several promising research directions may be explored:

- **Scaling Effects:** Investigating how the proposed methodology performs when applied to larger foundation models.
- **Modality Expansion:** Exploring the potential integration of additional modalities (e.g., audio, video) into the unified embedding space using similar principles.
- **Application Studies:** Examining the practical benefits of the proposed embeddings in downstream applications such as multimodal retrieval systems and document understanding platforms.
- **Architectural Refinements:** Further research into attention mechanisms, projection head designs, and loss formulations to enhance representation quality.
- **Adaptive Prefix Inference:** Developing mechanisms that could automatically infer the most appropriate prefix during inference time based on input characteristics, potentially offering task-optimized embeddings without requiring explicit user specification.
- **Theoretical Analysis:** Deeper mathematical analysis of how different loss functions shape the embedding space geometry and how prefix-guided conditioning mediates between potentially conflicting geometric constraints.
- **Projection Architecture Optimization:** Investigating optimal depth, width, and activation functions for the projection head to balance expressivity with computational efficiency.

We hope that the principles and methodologies proposed in this work contribute to the ongoing conversation about efficient, versatile multimodal representations, particularly for complex inputs that span multiple modalities.

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