

β -CLIP: Text-Conditioned Contrastive Learning for Multi-Granular Vision-Language Alignment

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Abstract

*CLIP achieves strong zero-shot image-text retrieval by aligning global vision and text representations, yet it falls behind on fine-grained tasks even when fine-tuned on long, detailed captions. In this work, we propose β -CLIP, a multi-granular text-conditioned contrastive learning framework designed to achieve hierarchical alignment between multiple textual granularities—from full captions to sentences and phrases—and their corresponding visual regions. For each level of granularity, β -CLIP uses cross-attention to dynamically pool image patches into contextualized visual embeddings. To address the semantic overlap inherent in this hierarchy, we introduce the β -Contextualized Contrastive Alignment Loss (β -CAL), which parameterizes the trade-off between query-specific matching and intra-image contextualization under both Cross-Entropy and Binary Cross-Entropy formulations. Through extensive experiments, we demonstrate that β -CLIP significantly improves dense alignment, achieving **91.8% T2I** **92.3% I2T** at **R@1** on **Urban1K** and **30.9%** on **FG-OVD (Hard)**, setting state-of-the-art among methods trained without hard negatives. β -CLIP establishes a robust, adaptive baseline for dense vision-language correspondence. The code and models are released at <https://github.com/fzohra/B-CLIP>.*

1. Introduction

Vision-language models such as CLIP [22] have transformed multimodal learning by aligning visual and textual representations in a shared latent space, enabling zero-shot capabilities across diverse tasks such as retrieval, classification, detection, and segmentation in various domains [14, 15, 25, 32, 34, 40]. More recently, CLIP has been widely adopted as either a vision or text backbone in generative models for tasks including captioning, visual question answering (VQA), and even image generation [7, 16, 20, 23, 24, 37]. However, in the era of long texts, CLIP faces two primary bottlenecks: a fixed context length

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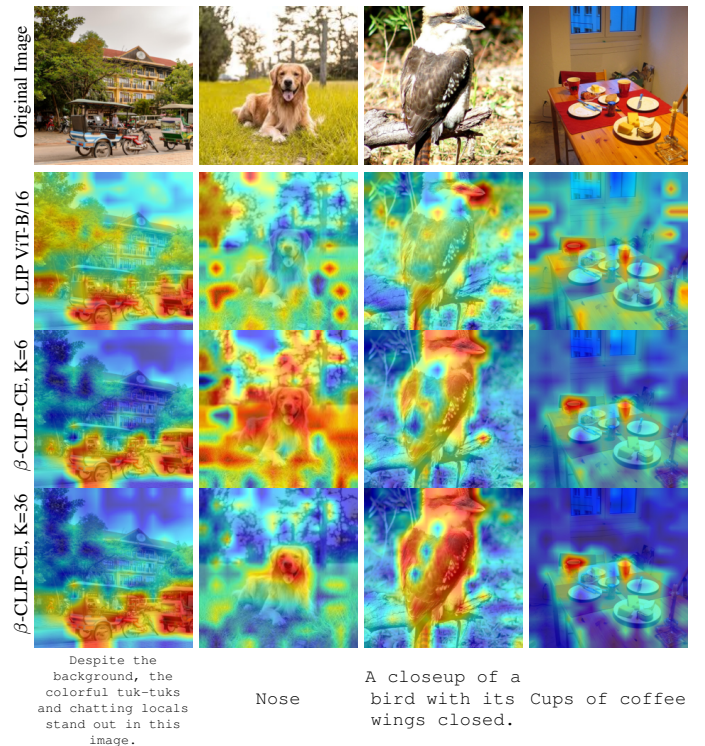


Figure 1. Heatmaps of patch-text logit similarities. Compared to pretrained CLIP’s diffuse global activations, training with 5-sentences ($K = 6$) enhances localized peaks for holistic scenes (e.g., tuk-tuks) but shows less precise localization for granular details (e.g., dog’s nose); using an additional 30-concept ($K = 36$) yields spatially precise, high-contrast activations for the semantic features (e.g., nose, coffee cups). BCE variants in Supplementary Material.

of only 77 tokens and a contrastive training objective that captures coarse, global alignments between entire images and captions [28, 36]. Although this global alignment effectively captures broad semantics, and to some extent fine-grained semantics as well [3], it provides no direct mechanism to associate specific visual regions with fine-grained text. Extending CLIP to accommodate expansive contexts and granular alignments remains a significant challenge.

Prior efforts to address CLIP’s coarse-grained limitations have focused on localizing visual concepts in increasingly abstract ways. The most direct approaches explicitly align region-level features with text, for example through early works like Region-CLIP [39], which pairs image crops with phrase-level text, and more recent advances like FG-CLIP [30], which scales alignment by constructing a corpus of 1.6B long captions and 40M region-level boxes and training RoI features to contrast with phrases.

Moving beyond explicit regions, patch-text alignment methods more abstractly refine these correspondences by grouping vision patches with text tokens—typically using similarity measures or heuristics for averaging [4, 17, 33] or through trainable modules for aggregating patches and text tokens as in [1]. Notably, DreamLIP [38] observed that sentences within MLLM-generated long captions often describe only partial aspects of an image—such as a specific object or scene. Rather than relying on region-level supervision or explicit token grouping, it decomposes each long caption into sub-captions to create multiple positive text pairs, aligning them globally with a multi-positive contrastive loss and locally via cosine-similarity-based patch pooling. FLAIR [29] advances this idea by replacing the cosine-based pooling with text-conditioned attention pooling that extracts patch features specific to a given query.

In this work, we adapt FLAIR’s attention pooling to select visual features for a *hierarchy of textual queries*. Specifically, β -CLIP decomposes long captions into constituent sentences and phrases, replacing standard pooling with a shallow Transformer block modified for Cross-Attention Pooling. This refines query–patch interactions to improve fine-grained selection while retaining broader context. By densely probing visual features at multiple granularities, our method concentrates attention on fine-grained details where global representations exhibit poor separability. Unlike FLAIR, which relies on text-conditioned pooling at both training and inference, β -CLIP uses it only during training and reduces to standard CLIP at inference, preserving its caching efficiency. However, training with multi-granular queries poses unique challenges for contrastive learning due to semantic overlap across granularities. Unlike traditional region alignment—where local regions explicitly align with queries—our pooled features are inherently contextualized within global image semantics, as cross-attention preserves contributions from contextual patch tokens.

To handle overlapping semantics, we propose a β -contextualized contrastive alignment loss (β -CAL): a parameterized contrastive objective that treats all feature pairs from the same image as positives. The objective is controlled by a weighting factor $\beta \in [0, 1]$, that interpolates between strict and relaxed positive alignments across two contrastive variants—a soft Cross-Entropy (CE) form or a

hard Binary Cross-Entropy (BCE) form. Specifically, at $\beta = 0$, it enforces strict self-matching (treating only the most precise intra-image pair as a full positive) to prioritize sharp, fine-grained alignments; at higher β values (approaching 1), it promotes more uniform competition among all these intra-image positives—tuning soft probability targets in the CE variant or β -weighted gradients in the BCE variant—to better integrate contextual information without diluting specificity.

Our primary contributions are summarized as follows:

- We propose β -CLIP, a multi-granular text-conditioned contrastive learning framework that densely aligns image representations with hierarchical text descriptions, demonstrating the effectiveness of probing visual features at multiple granularities for fine-grained understanding.
- We introduce a β -weighted contrastive objective (β -CAL) to address overlapping semantics in text-conditioned patch pooling. This objective supports both smooth-target cross-entropy and hard-target binary cross-entropy losses, enabling fine-grained learning from long captions.
- We validate β -CLIP by fine-tuning CLIP on long-text and image pairs from ShareGPT4V, yielding significant improvements on the challenging fine-grained and long-text retrieval benchmarks FG-OVD, DCI, and Urban1K, without relying on hard negatives.
- We identify a trade-off between specificity and contextualization when training on long captions, which can lead to overfitting in long-text retrieval tasks. We demonstrate that this issue affects different types of losses differently and can be navigated using the β -CAL loss.

2. Related Work

2.1. Fine-Grained Vision-language Alignment

CLIP’s single global image embedding has motivated many approaches to incorporate fine-grained vision-text alignment in diverse ways. For explicit region-text alignment, RegionCLIP [39] mines pseudo region–caption pairs for regional contrastive learning, while FineCLIP [12] combines object crops with VLM-generated region captions and self-distillation to supervise patch-level features. FG-CLIP [30] scales this paradigm with tens of millions of region captions, long descriptions, and hard compositional negatives. Other methods avoid explicit bounding boxes entirely: FILIP [33] and PACL [17] introduce token-wise or patch-based alignment, while SPARC [4] learns sparse groupings of patches for specific tokens. Recently, [21] showed that naively projecting all patch tokens into text space can collapse spatial correlations despite strong retrieval performance. Moving beyond such projections, recent works have shifted toward text-conditioned feature selection, where the text query dynamically selects rele-

vant visual features. FLAIR [29] applies text-conditioned cross-attention to pool specific patch features, while SmartCLIP [31] learns a binary mask over visual embeddings to select feature dimensions most relevant to the text. [3] provides a complementary view of CLIP’s fine-grained limitations, showing that while attributes such as color, material, and patterns are present in its embeddings, contrastive pretraining biases the latent space toward coarse, category-level semantics. This suggests that CLIP’s shortcomings stem not from a lack of localization alone, but from its latent representation, motivating methods that better disentangle fine-grained attributes within the shared image–text space.

2.2. Long Captions in CLIP

CLIP is pre-trained with a 77-token text window, which limits its use with long descriptions. [26] show that CLIP-based models underutilize rich visual detail and introduce DCI—human-annotated, mask-aligned captions that are $\approx 1k$ words in length—along with a summarized variant, sDCI, that fits within 77 tokens. Fine-tuning CLIP on the small sDCI set (with LLM-generated summaries and negatives) yields improvements on fine-grained discrimination. Similarly efforts have been made by DOCCI [19] to increase fine-grained details in captions and DreamLIP [38] and ShareGPT4V [5] with synthetically generated long captions. Using ShareGPT4V captions, LongCLIP [36] shows that by fixing the first 20 positional embeddings and 4x interpolating the rest, CLIP can be fine-tuned to handle longer captions (up to 248 tokens), partially mitigating the context-length bottleneck; this approach is being increasingly adopted [1, 30, 31], as do we. TULIP [18] replaces absolute encodings with relative ones and uses distillation plus long-caption finetuning to finetune CLIP to arbitrary token lengths. Interestingly, [28] observe that training with long captions boosts long-text retrieval but degrades short-text retrieval; they subsequently propose using learnable tokens in the text encoder to aggregate diverse features via attention masks, which helps recover short-text performance. In our work, we also observe this phenomena in the CE variants, and observe that the BCE variants can help mitigate this.

3. Methodology

Our approach extends CLIP for fine-grained, multi-granular alignment by decomposing each caption into sentence- and phrase-level queries. These queries guide text-conditioned attention pooling—implemented with a shallow modified Transformer block—to extract scale-specific features. We align these features using the β -contextualized contrastive alignment loss (β -CAL), which balances fine-grained precision with contextual integration. Figure 2 provides an overview.

3.1. Hierarchical Text Decomposition

Given an image–caption pair (I, C) , we decompose the caption into three semantic scales.

Caption level: The full caption provides global context:

$$\mathbf{t}_{\text{cap}} = f_{\text{text}}(C) \in \mathbb{R}^D,$$

where f_{text} is the CLIP text encoder.

Sentence-Level: We segment the caption into K_{sent} individual sentences for coarse-grained semantics:

$$\{\mathbf{t}_{\text{sent}}^i\}_{i=1}^{K_{\text{sent}}} = \{f_{\text{text}}(s_i) : s_i \in \text{split}(C)\}.$$

Phrase-Level: We extract K_{phrase} key concepts (noun phrases and verb phrases) using dependency parsing (via spaCy [11]) for localized/fine-grained semantics:

$$\{\mathbf{t}_{\text{phrase}}^j\}_{j=1}^{K_{\text{phrase}}} = \{f_{\text{text}}(p_j) : p_j \in \text{extract}(C)\}.$$

This yields $K = 1 + K_{\text{sent}} + K_{\text{phrase}}$ text embeddings per image, forming the multi-scale text representation $\mathbf{T} = [\mathbf{t}_1, \dots, \mathbf{t}_K] \in \mathbb{R}^{K \times D}$. Since the CLIP text encoder is trained with a causal mask, we need to extract the EOS token for each text query rather than simply reusing the corresponding text tokens from the full caption.

3.2. Multi-Granularity Visual Feature Selection

For the input image I , we extract patch embeddings using the CLIP vision transformer using the approach from [8], skipping the $Q - K$ mixing in the final attention block for the patch tokens of the ViT to preserve localized features:

$$[\mathbf{v}_{\text{CLS}}; \mathbf{P}] = f_{\text{vision}}(I) \in \mathbb{R}^{(N+1) \times D},$$

where $\mathbf{P} = [\mathbf{p}_1, \dots, \mathbf{p}_N]$ are the patch tokens and N is the number of visual patches ($N = 196$ for ViT-B/16) and $\mathbf{v}_{\text{CLS}} \in \mathbb{R}^D$ is the global image token. We then generate K text-conditioned image embeddings via cross-attention pooling. For each text query $\mathbf{t}_k \in \mathbf{T}$, we compute attention weights over the patches:

$$\begin{aligned} \mathbf{Q}_k &= \mathbf{t}_k \mathbf{W}_Q, \quad \mathbf{K} = \mathbf{P} \mathbf{W}_K, \quad \mathbf{V} = \mathbf{P} \mathbf{W}_V, \\ \alpha_k &= \text{softmax}\left(\frac{\mathbf{Q}_k \mathbf{K}^\top}{\sqrt{D/h}}\right), \quad \mathbf{v}_k = \alpha_k \mathbf{V}. \end{aligned} \quad (1)$$

where $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V \in \mathbb{R}^{D \times D}$ are learned projections, $h = 8$ is the number of attention heads, and D/h is the head dimension. The Transformer block is modified to skip the first residual connection around the multi-head self-attention layer. Instead, after computing the attention-weighted values, the model directly normalizes and applies a 2-layered MLP to each query-specific value vector $\mathbf{v}_k$, followed by a residual connection. This produces query-specific visual representations $\mathbf{V} = [\mathbf{v}_1, \dots, \mathbf{v}_K] \in \mathbb{R}^{K \times D}$, where each $\mathbf{v}_k$ attends to visual regions relevant to $\mathbf{t}_k$.

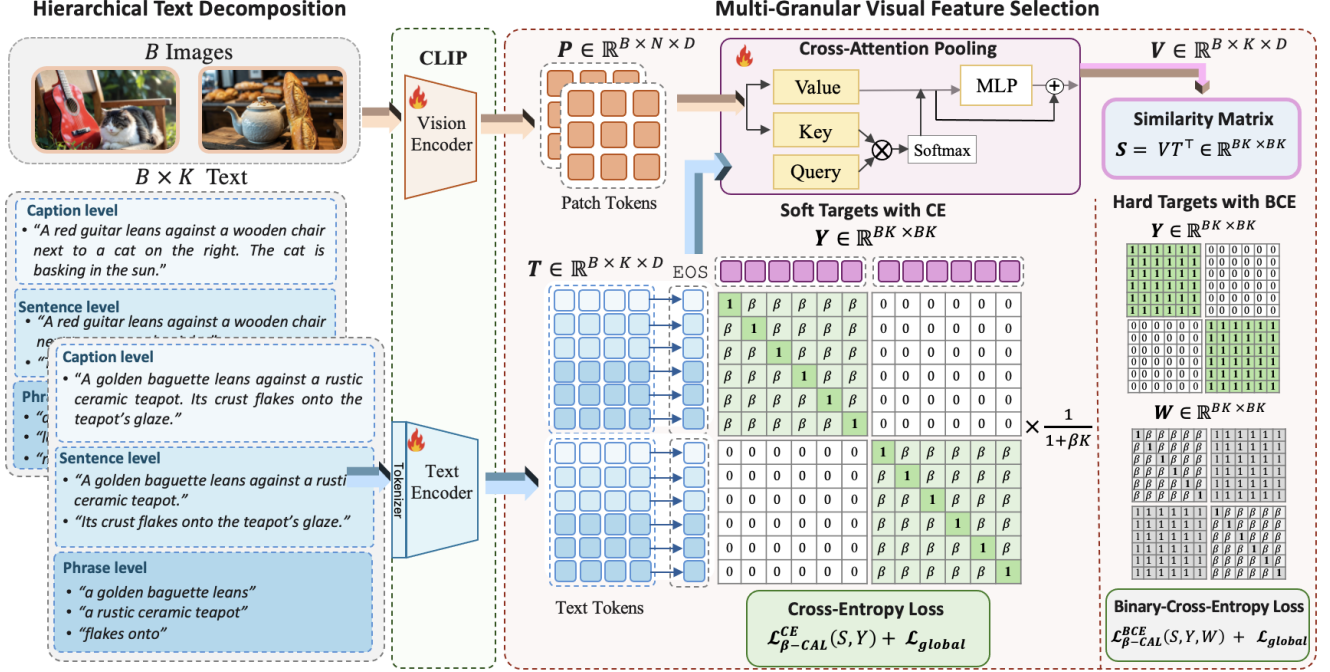


Figure 2. **Overview of the β -CLIP architecture** ($B = 2$ and $K = 6$ shown for illustrative purposes). For each image, the text is decomposed into K multi-granular inputs and independently encoded using the CLIP vision and text encoders respectively. The patch tokens $\mathbf{P}$ (orange) and EOS tokens $\mathbf{T}$ (blue) serve as the keys/values and queries to compute the multi-granular, text-conditioned visual embeddings $\mathbf{V}$ (purple) via the **cross-attention pooling block**. We compute the similarities between the flattened text tokens $\mathbf{T}$ and the flattened text-conditioned visual embeddings $\mathbf{V}$ and symmetrically apply β -CAL using either normalized **soft targets with cross-entropy (CE)** or **hard targets with binary cross-entropy (BCE)**. For BCE, the β -weights are applied to loss as described in Eq. (5). We omit the visualizations for the CLS tokens and the details of the global loss for the CLS tokens and caption-level text EOS tokens.

3.3. β -Contextualized Contrastive Alignment Loss

Since the hierarchical features introduce semantic overlaps, phrase features $\mathbf{v}_j^{phrase}$ may subsume parts of sentence features $\mathbf{v}_i^{sent}$. Given this contextualization, we treat *all* intra-image feature pairs as positives with tunable overlap via $\beta \in [0, 1]$. For a batch of B images, both variants construct a flattened similarity matrix $\mathbf{S} \in \mathbb{R}^{BK \times BK}$ where $S_{ij} = \mathbf{v}_i^T \mathbf{t}_j / \tau$, and τ is a learned temperature. We then apply β differently for each variant: in the soft Cross-Entropy (CE) form, it interpolates probabilistic targets; in the hard Binary Cross-Entropy (BCE) form, it modulates gradient weights on binary positives, as detailed below.

3.3.1. Soft Targets with Cross-Entropy

To form the training targets, we first define the target weights w_{ij} , which represent the desired strength of alignment between features i and j . These weights label exact matches as positives, related intra-image pairs as tunable soft positives modulated by β , and cross-image pairs as negatives:

$$w_{ij} = \begin{cases} 1 & \text{if } i = j \text{ (positive)} \\ \beta & \text{if } \lfloor i/K \rfloor = \lfloor j/K \rfloor, i \neq j \text{ (intra-image positives)} \\ 0 & \text{otherwise (cross-image negatives)} \end{cases} \quad (2)$$

and row-normalize them to get a soft distribution

$$p_{ij} = \frac{w_{ij}}{\sum_{l=1}^{BK} w_{il}}.$$

We use these weights in lieu of the labels. Per standard Cross-Entropy, we apply *softmax* to the similarities $\mathbf{S}$ to yield predicted probability distributions q_{ij}^{v2t} and q_{ji}^{t2v} . The β -CAL loss is computed as the symmetric cross-entropy [27]:

$$\begin{aligned} \mathcal{L}_{v2t}^{CE} &= -\frac{1}{BK} \sum_{i,j} p_{ij} \log q_{ij}^{v2t}, \\ \mathcal{L}_{t2v}^{CE} &= -\frac{1}{BK} \sum_{i,j} p_{ij} \log q_{ji}^{t2v}, \\ \mathcal{L}_{\beta-CAL}^{CE} &= \frac{1}{2} (\mathcal{L}_{v2t}^{CE} + \mathcal{L}_{t2v}^{CE}) \end{aligned} \quad (3)$$

These soft interpolated weights promotes exact self-alignment (via the diagonal $w_{ij} = 1$) while controlling the alignment of contextual information from related intra-image features (via β). When $\beta = 0$, only exact matches contribute; as β increases to 1, the full intra-image set acts as positives. The softmax step ensures the predictions form a valid probability distribution over all possible pairs. The complete objective combines β -CAL with standard CLIP

loss where the $\mathcal{L}_{\text{global}}$ is applied to the similarities between the global image tokens and the full caption tokens respectively:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\beta\text{-CAL}} + \mathcal{L}_{\text{global}}.$$

3.3.2. Hard Targets with Binary Cross-Entropy

In the Binary Cross Entropy formulation, the targets $\mathbf{Y} = \{y_{i,j}\}$ remain strictly binary such that *all* intra-image pairs are positives:

$$y_{ij} = \begin{cases} 1 & \text{if } \lfloor i/K \rfloor = \lfloor j/K \rfloor \\ 0 & \text{otherwise,} \end{cases}$$

The similarities $\mathbf{S}$ are passed through a *sigmoid* activation to yield independent binary probabilities $q_{ij}^{\text{v2t}} = \sigma(S_{ij})$ and $q_{ji}^{\text{t2v}} = \sigma(S_{ji})$ [35]. The weights $\mathbf{W} = \{w_{i,j}\}$ for modulating the loss are computed as:

$$w_{ij} = \begin{cases} 1 & \text{if } i = j \text{ (positive)} \\ \beta & \text{if } \lfloor i/K \rfloor = \lfloor j/K \rfloor, i \neq j \text{ (intra-image positives)} \\ 1 & \text{otherwise (cross-image negatives)} \end{cases} \quad (4)$$

We then compute the symmetric BCE loss as:

$$\begin{aligned} \mathcal{L}_{\text{v2t}}^{\text{BCE}} &= -\frac{1}{BK} \sum_{i,j} w_{ij} [y_{ij} \log q_{ij}^{\text{v2t}} + (1 - y_{ij}) \log (1 - q_{ij}^{\text{v2t}})], \\ \mathcal{L}_{\text{t2v}}^{\text{BCE}} &= -\frac{1}{BK} \sum_{i,j} w_{ij} [y_{ji} \log q_{ji}^{\text{t2v}} + (1 - y_{ji}) \log (1 - q_{ji}^{\text{t2v}})], \\ \mathcal{L}_{\beta\text{-CAL}}^{\text{BCE}} &= \frac{1}{2} (\mathcal{L}_{\text{v2t}}^{\text{BCE}} + \mathcal{L}_{\text{t2v}}^{\text{BCE}}). \end{aligned} \quad (5)$$

The weights w_{ij} (from Eq. 4) scale each pair’s contribution. In this way, this BCE formulation assigns binary positives to all intra-image pairs, but modulates their gradient contributions via β , downweighting off-diagonal terms when $\beta < 1$. By scaling the influence of these contextual positives, it provides an alternative way to navigate the precision-generalization trade-off.

3.4. The Role of β

The parameter β controls the balance between query-specific precision and intra-image contextualization. As $\beta \rightarrow 0$, the target concentrates on the self-match, yielding text-specific features but collapsing multi-scale representations. As $\beta \rightarrow 1$, target mass spreads uniformly across intra-image positives, encouraging cross-scale consistency, but potentially diluting query-specific signals. This trade-off is captured by the diagonal fraction $f_{\text{diag}} = 1/(1 + (K - 1)\beta)$, which determines how much target mass is assigned to the self-match relative to other intra-image positives.

4. Experiments

We evaluate β -CLIP on fine-grained, long-text, and coarse-grained retrieval tasks. Models are fine-tuned on a safety-

filtered subset of ShareGPT4V-1.24M¹ using AdamW with learning rates of 10^{-5} for the pre-trained parameters and 10^{-3} for the added Transformer block, an effective batch size of 2048 (per-GPU batch size of 64, 4 A100 GPUs, 8 gradient accumulation steps), and 10 training epochs. We note that because each image is paired with K captions of varying granularity, the resulting similarity matrix is of size $BK \times BK$, meaning each image is compared against significantly more negatives than the nominal batch size suggests. See Supplementary for more details.

4.1. Fine-Grained Retrieval

FG-OVD [2] evaluates fine-grained alignment using region-level queries derived from bounding-box annotations. Each region is paired with a positive description and ten hard negatives as semantic distractors. Performance is measured across four difficulty splits—Trivial, Easy, Medium, and Hard. Following [30], we extract region features using RoI pooling over patch embeddings and compute alignment via cosine similarity to text queries. Baselines highlight the task’s difficulty: CLIP achieves 12.0% on the Hard split, while region-supervised methods such as FG-CLIP reach 46.1% when trained with hard-negatives.

As shown in Table 1, the β -CLIP variants outperform CLIP and other baselines on fine-grained retrieval benchmarks. With the Cross-Entropy (CE) objective, accuracy increases sharply from the CLIP baseline across all FG-OVD splits, surpassing the region-aligned Fine-CLIP by +4.1, +5.6, +10.0, and +8.4 points on the Hard, Medium, Easy, and Trivial splits, respectively. Notably, β -CLIP outperforms all methods trained on the same ShareGPT4V-1M data—such as Long-CLIP and Smart-CLIP—demonstrating that data alone does not account for the performance increase. We further observe the effectiveness of our multi-granular text-conditioned approach when compared to the region-aligned FG-CLIP^{††}. Despite using significantly less training data (1.2M vs. 1.6B+12M+50M region proposals) and training without hard negatives, the β contextualized alignment allows us to recover 55% of the performance gap between standard CLIP and FG-CLIP—calculated as the ratio of our absolute gain over CLIP to the FG-CLIPs absolute gain over CLIP.

4.2. Long-Text Retrieval

We evaluate zero-shot retrieval on extended captions using the DCI, SV-1k, and Urban-1k benchmarks, where long descriptions challenge CLIP’s 77-token limit and its global alignment objective. DCI [26] provides dense, region-level narratives spanning multiple entities per image. SV-1k [5] contains 1K validation ShareGPT4V captions and serves

¹We remove $\approx 2K$ image-text pairs containing abusive content using Detoxify [10] for text and FalconsAI [9] for images (full filtering details in Supplementary).

Method	Data	Fine-Grained Retrieval				Long-Text Retrieval					
		FG-OVD				DCI		SV-1k		Urban-1k	
<i>ViT-B/16</i>		Hard	Medium	Easy	Trivial	T2I	I2T	T2I	I2T	T2I	I2T
CLIP	WIT-400M	12.0	23.1	22.2	58.5	43.0	45.5	79.6	78.2	53.2	67.5
EVA-CLIP	Merged-2B [†]	14.0	30.1	29.4	58.3	41.2	41.9	85.5	90.5	-	-
SigLIP	WebLI-1B	-	-	-	-	56.2	57.7	83.4	85.8	62.1	62.7
Fine-CLIP	CC2.5M + 10.4M reg.	<u>26.8</u>	<u>49.8</u>	<u>50.4</u>	<u>71.9</u>	34.4	35.5	73.3	70.6	-	-
LoTLIP	Mixed-100M [§]	-	-	-	-	61.0	62.1	86.8	95.5	-	-
FLAIR*	DreamLIP 30M	13.3	27.5	28.6	79.3	66.2	61.3	98.0	98.5	87.7	83.6
FG-CLIP [‡]	WIT-400M + LAION-1.6B + GRIT-12M + 40M reg.	24.5	47.1	49.5	-	-	-	-	-	-	-
FG-CLIP ^{††}	+10M hard negatives	46.1	66.6	68.7	83.4	60.6	61.8	94.9	96.7	89.9	93.0
<i>Methods fine-tuning CLIP on WIT-400M + ShareGPT4V-1M</i>											
Long-CLIP*		9.2	18.4	16.2	51.8	57.4	51.8	93.4	94.7	79.5	78.9
TULIP	WIT-400M	-	-	-	-	50.6	50.2	98.6	98.6	86.6	88.1
FineLIP	+ ShareGPT4V-1M	-	-	-	-	-	-	89.3	90.7	87.4	<u>90.0</u>
Smart-CLIP*		18.9	37.0	37.9	70.1	64.5	65.3	<u>98.1</u>	98.7	87.4	<u>90.0</u>
<i>Ours: β-CLIP</i>											
K=36, $\beta=0.5$, CE	WIT-400M	30.9	55.4	60.4	80.3	59.9	58.4	93.7	94.0	<u>89.0</u>	88.6
K=36, $\beta=0.5$, BCE	+ ShareGPT4V-1M	20.1	38.5	34.2	71.3	<u>65.1</u>	<u>63.6</u>	94.4	94.1	91.8	92.3

Table 1. Performance on fine-grained and long-text retrieval tasks. [‡] denotes FG-CLIP trained **without** 10M hard negatives while ^{††} denotes FG-CLIP trained **with 10M hard negatives**. We gray out FG-CLIP for fair comparison with our method, which does not use Hard Negatives during training. [†] marks models trained on a dataset combining 1.6B LAION-2B and 0.4B COYO-700M samples. [§] refers to a 100M-image recaptioned dataset (CC3M, CC12M, YFCC15M, LAION, COYO). “reg.” denotes the use of additional region-level supervision. * indicates models we evaluate: SmartCLIP (FG-OVD, DCI), LongCLIP (DCI), and FLAIR (FG-OVD).

as an in-distribution evaluation. Urban-1k [36] comprises visually similar urban scenes from Visual Genome [13], each paired with a GPT-4V-generated caption averaging 107 words. As shown in table 1, β -CLIP (BCE) establishes a new state-of-the-art on the Urban-1k benchmark, achieving **91.8%** (T2I) and **92.3%** (I2T). Notably, it outperforms models specifically designed for long-text understanding trained on the same data, including Smart-CLIP (87.4% T2I) and Long-CLIP (79.5% T2I). On the DCI benchmark, which requires understanding multiple entities and relationships, β -CLIP achieves 65.1% R@1, surpassing Long-CLIP by a wide margin (+7.7%) and performing comparably to FLAIR and SmartCLIP.

4.3. Coarse-Grained Retrieval

Standard coarse-grained retrieval is evaluated on short-caption datasets (MSCOCO and Flickr30k) to assess whether multi-granular training preserves CLIP’s global alignment behavior. Across both datasets, methods that rely on sigmoid-based objectives—notably SigLIP and FLAIR—consistently outperform CLIP and other CE-based variants, suggesting that optimizing for independent binary matching helps with coarse-grained retrieval.

As shown in Table 2, the CE-based β -CLIP model performs comparably to the CLIP baseline. In contrast, the

BCE variant of β -CLIP consistently achieves stronger performance on these tasks, surpassing both the CE variant and the CLIP baseline. Notably, whereas prior work has shown that naively fine-tuning on detailed captions can degrade short-text alignment [28, 36], our BCE variant maintains absolute gains over the CLIP baseline on both MSCOCO (+6.7 T2I and +1.5 I2T R@1) and Flickr30k (+7.7 T2I and +1.5 I2T R@1), comparable to the improvements achieved by dedicated long-caption methods such as LongCLIP and SmartCLIP.

5. Ablations

We ablate the main components of β -CLIP: the alignment objective, β , hierarchy size K , and text-conditioning strategies.

Contextualized Contrastive Alignment. Table 3 isolates the impact of our proposed objective by comparing standard fine-tuning against β -CLIP. We apply Symmetric Cross-Entropy (CE) with either a single positive ($K=1$) long caption or strictly intra-image positive sentences ($K=6$). Direct fine-tuning without text-conditioning demonstrates a limited capacity to leverage multiple positives. In contrast, applying the β -CAL objective (with $\beta=0.5$) increases

Method	Data	Coarse-Grained Retrieval							
		MSCOCO				Flickr30k			
		T2I		I2T		T2I		I2T	
		R@1	R@5	R@1	R@5	R@1	R@5	R@1	R@5
<i>ViT-B/16</i>									
CLIP	WIT-400M	33.1	58.4	52.5	76.7	62.1	85.6	81.9	96.2
SigLIP	WebLI-1B	<u>47.2</u>	<u>72.1</u>	<u>65.5</u>	<u>86.2</u>	<u>75.6</u>	<u>92.8</u>	89.1	98.6
FineCLIP	WIT-400M + CC2.5M + 10.4M reg.	40.2	66.5	54.5	78.6	67.9	89.1	82.5	96.4
LoTLIP	Mixed-100M	38.06	63.81	59.66	81.50	65.22	87.98	86.90	97.80
DreamLIP	DreamLIP-30M	44.8	69.8	62.3	84.5	73.3	91.8	89.9	<u>99.0</u>
FLAIR		53.3	77.5	68.0	87.8	81.1	94.9	94.7	99.3
FG-CLIP	WIT-400M + LAION-1.6B + GRIT-12M + 40M reg + 10M hard negatives	45.4	-	64.1	-	76.4	-	90.7	-
<i>Methods fine-tuning CLIP on WIT-400M + ShareGPT4V-1M</i>									
TULIP		40.7	66.1	56.8	80.3	-	-	-	-
LongCLIP*		40.4	65.8	57.6	81.1	70.4	90.5	84.1	98.0
SmartCLIP*	WIT-400M	42.4	68.2	61.9	83.3	72.5	91.4	<u>90.1</u>	98.4
β -CLIP K=36, $\beta=0.5$, CE	+ ShareGPT4V-1M	34.0	60.2	46.0	74.2	62.6	87.1	73.2	95.2
β -CLIP K=36, $\beta=0.5$, BCE		39.8	66.0	54.0	79.3	69.8	90.5	83.4	97.2

Table 2. β -CLIP variants largely preserve CLIP’s coarse-grained retrieval performance on MSCOCO and Flickr30k, avoiding the degradation typically observed when fine-tuning CLIP on long text. * denotes our evaluation on Flickr30k using [6].

FG-OVD performance by 7–12 points across the Hard, Medium, and Easy splits compared to the baseline. Interestingly, at K=1 $\beta=0$ where no sub-caption hierarchy is used but text-conditioning is still present—CE and BCE perform similarly (Hard: ≈ 22 , U-1k: ≈ 88). The distinction emerges once hierarchy is introduced. Although both losses benefit from hierarchical supervision, they interact with it differently. CE improves fine-grained discrimination (Hard: 22 $\rightarrow$ 29.2 at K=6), whereas BCE favors long-text retrieval (U-1k: 87.6 $\rightarrow$ 91.8, 89.5 $\rightarrow$ 92.0 at K=6).

Method	FG-OVD				SV-1k		U-1k	
	Hard	Medium	Easy	Trivial	T2I	I2T	T2I	I2T
<i>finetuning with CLIP’s global loss</i>								
Single positive, K=1	22.0	44.6	44.2	69.6	93.8	94.3	88.6	88.3
Multiple positive, K=6	19.7	40.1	40.8	67.2	93.9	93.5	89.0	87.5
<i>β-CLIP</i>								
CE K=1, $\beta=0$	22.0	46.3	44.5	72.7	93.9	94.2	88.4	89.2
BCE K=1, $\beta=0$	21.3	44.7	43.6	70.9	94.1	94.3	87.6	89.5
CE K=6, $\beta=0.5$	29.2	51.3	56.4	81.5	93.5	94.0	87.9	88.4
BCE K=6, $\beta=0.5$	20.6	42.7	45.3	71.2	94.5	94.0	91.8	92.0

Table 3. Comparison of baseline methods fine-tuning CLIP on long-text without text-conditioning. K=1 includes only the long caption, K=6 includes long-caption and sentence-level captions.

The Specificity–Contextualization Trade-off. The hyperparameter β governs the trade-off between diagonal specificity and off-diagonal contextualization discussed in Section 3.4. Table 4 illustrates this dynamic. At $\beta = 0$, the loss focuses strictly on self-matching, which favors long-text retrieval but yields poor fine-grained performance.

Method	FG-OVD					SV-1k		U-1k		Sim
	<i>ViT-B/16</i>	Hard	Medium	Easy	Trivial	T2I	I2T	T2I	I2T	
β -CLIP (CE)										
$\beta=0$	3.6	7.1	8.9	11.5	94.4	93.8	90.7	91.4	0.14	
$\beta=0.1$	23.2	45.3	48.9	77.5	94.0	94.1	89.2	87.9	0.92	
$\beta=0.15$	27.8	51.0	56.4	79.4	93.7	94.3	88.5	87.9	0.94	
$\beta=0.5$	30.9	55.4	60.4	80.3	93.7	94.0	89.0	88.6	0.98	
$\beta=1$	30.8	54.4	59.0	80.6	93.4	94.1	88.7	88.7	0.98	
β -CLIP (BCE)										
$\beta=0$	14.8	30.1	31.8	64.6	94.0	94.3	91.9	91.6	0.66	
$\beta=0.25$	18.1	35.6	30.0	72.8	94.2	94.1	92.1	91.9	0.96	
$\beta=0.5$	20.1	38.5	34.2	71.3	94.4	94.1	91.8	92.3	0.98	
$\beta=0.75$	19.8	38.0	34.2	72.8	94.3	93.8	91.8	91.8	0.98	
$\beta=1$	20.2	40.4	36.3	70.4	94.3	93.9	92.0	91.9	0.98	

Table 4. Effect of varying β at $K = 36$. β controls the specificity–contextualization tradeoff between diagonal specificity and off-diagonal contextualization.

Both CE and BCE rely on $\beta > 0$ for fine-grained gains: CE Hard accuracy rises from 3.6% to 30.9% at $\beta = 0.5$, while BCE Hard increases from 14.8% to 20.2% at $\beta = 1$. The two losses differ, however, in their sensitivity on long-text retrieval: CE incurs minor drops ($< 1\%$) as β increases, whereas BCE remains largely unaffected. Similar trends hold at $K=6$ (see Supplementary).

Increasing Fine-Grained Semantics for Multi-Granular Alignment. Table 5 analyzes the impact of increasing the number of positive phrases. We observe that increasing K from 6 to 36 improves performance on the Hard split by +1.7 points (reaching 30.9%), with even larger gains of +4.1 and +4.0 on the Medium and Easy splits, respectively.

Method	FG-OVD				DCI		SV-1k		U-1k	
	Hard	Medium	Easy	Trivial	T2I	I2T	T2I	I2T	T2I	I2T
<i>β-CLIP (CE)</i>										
K=6, $\beta=0.5$	29.2	51.3	56.4	81.5	56.0	51.5	93.5	94.0	87.9	88.4
K=16, $\beta=0.5$	29.2	52.2	58.6	80.8	59.7	56.5	93.3	94.5	88.1	87.9
K=36, $\beta=0.5$	30.9	55.4	60.4	80.3	59.9	58.4	93.7	94.0	89.0	88.6
<i>β-CLIP (BCE)</i>										
K=6, $\beta=0.5$	20.6	42.7	45.3	71.2	64.9	62.7	94.5	94.0	91.8	92.0
K=16, $\beta=0.5$	20.9	42.7	41.6	71.0	65.2	63.2	94.0	94.2	92.2	91.8
K=36, $\beta=0.5$	20.1	38.5	34.2	71.3	65.1	63.6	94.4	94.1	91.8	92.3

Table 5. Effect of varying K . $K = 6$: 1 caption + 5 sentences; $K = 16$: +10 phrases; $K = 36$: +30 phrases.

This suggests that phrase-level text-conditioned features effectively localize fine-grained semantics, with performance on fine-grained FG-OVD improving as the number of descriptive phrases increases. Long-text retrieval similarly benefits from larger K , with DCI scores increasing by +3.9 (T2I) and +6.9 (I2T).

The BCE variant, however, shows a different pattern. It generally scores lower on FG-OVD than CE, and performance plateaus or diminishes as K increases (e.g., Easy split accuracy drops to 34.2% at $K = 36$). This pattern reflects BCE’s weaker fine-grained separation at $\beta=0.5$. This difference likely stems from the way the BCE loss defines its supervision: all intra-image pairs are treated as independent binary positives, with the loss for off-diagonal pairs downweighted by $\beta=0.5$. This encourages the model to distribute its focus across multiple related matches, thereby affecting its ability to distinguish precise query-image alignments from similar ones. Conversely, the CE variant generates a probability distribution over the logits (via softmax) in addition to normalized target weights, where intra-image positives compete against each other. This has the effect of encouraging the model to assign higher probabilities to exact matches. Despite this, BCE remains highly effective for long-text retrieval, consistently matching or surpassing CE across all K values (e.g., +5.2 to +5.5 gain on DCI T2I).

Inference With Text-Conditioned Image Representations. Table 6 compares long-text retrieval performance when using the text-conditioned image (TCI) representations, by conditioning each image embedding on its ground-truth caption, in lieu of the standard image CLS token. As shown, under the CE loss, TCI yields considerable improvements across both SV-1k and U-1k for $K = 6$ and $K = 36$, indicating that aligning image features to the specific query text greatly improves long-text matching. However, as K increases, the advantage of the TCI diminishes under binary cross-entropy (BCE) loss, which generally outperforms CE loss when using the CLS token.

Cross-Attention Pooling with Negative Text Queries. We explore the use of text-conditioned negatives, which in-

Method		SV-1k		U-1k	
<i>ViT-B/16</i>	Token	T2I	I2T	T2I	I2T
<i>β-CLIP (CE)</i>					
K=6, β =0.5	CLS	93.5	94.0	87.9	88.4
K=6, β =0.5	TCI	95.0	94.7	99.1	97.2
K=36, β =0.5	CLS	93.7	94.0	89.0	88.6
K=36, β =0.5	TCI	94.7	94.5	95.5	85.4
<i>β-CLIP (BCE)</i>					
K=6, β =0.5	CLS	91.8	92.0	94.5	94.0
K=6, β =0.5	TCI	94.9	94.6	97.0	95.3
K=36, β =0.5	CLS	91.8	92.3	94.4	94.1
K=36, β =0.5	TCI	93.9	93.2	88.9	83.6

Table 6. Effect of evaluating with text-conditioned image representations (TCI) on long-text retrieval instead of the standard CLS embedding.

			FG-OVD				SV-1k		U-1k		
C	S	P	Hard	Medium	Easy	Trivial	T2I	I2T	T2I	I2T	Sim
β -CLIP (CE)											
-	-	-	30.8	54.4	59.0	80.6	93.4	94.1	88.7	88.7	0.98
+ Text-Conditioned Negatives											
✓	✓		28.3	48.1	52.9	79.9	93.7	94.0	88.4	88.5	0.98
	✓	✓	28.9	52.3	55.4	80.9	93.6	93.9	87.6	88.3	0.97
✓	✓	✓	27.3	50.1	54.0	80.6	93.8	93.6	87.7	87.9	0.97
β -CLIP (BCE)											
-	-	-	20.2	40.4	36.3	70.4	94.3	93.9	92.0	91.9	0.98
+ Text-Conditioned Negatives											
✓	✓		22.2	44.1	40.2	73.1	94.3	94.0	91.1	92.1	0.98
	✓	✓	22.3	43.8	39.0	69.6	94.3	93.9	92.4	92.0	0.86
✓	✓	✓	22.5	44.2	43.3	72.9	94.1	94.1	91.8	92.4	0.85

Table 7. Effectiveness of *negative* hierarchical text conditioning at $K=36$ and $\beta=1$. Columns “C”, “S”, and “P” correspond to Caption, Sentence, and Phrase inputs, respectively.

roduce additional negative contrasts by sampling texts from specific hierarchy levels across other images in the batch. This approach supplements the positive text-conditioned representations with negative ones. These additional text-conditioned representations are then explicitly treated as negatives within the loss function by augmenting the standard set of negative pairs. As shown in Table 7, at $K = 36$, CE does not benefit from this type of conditioning. BCE, however, consistently improves FG-OVD and representation diversity while maintaining retrieval performance.

6. Conclusion

We introduced β -CLIP, a framework that aligns hierarchically decomposed text with text-conditioned visual features, enabling fine-grained multimodal understanding without region-level supervision. Through the β -CAL objective, we show that explicitly modeling intra-image granularity offers a strong alternative to region-supervised approaches for learning dense vision-language representations.

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