SAFE VISION-LANGUAGE MODELS VIA SPARSE AUTOENCODER FEATURE-GUIDED EMBEDDING STEERING

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ABSTRACT

Large vision language models such as CLIP provide transferable representations for retrieval, classification, generation, and visual question answering. However, pretraining on web data can also encode unsafe concepts that propagate to downstream systems. Existing safety alignment methods mainly follow two strategies. Fine tuning with constructed safe and unsafe pairs requires substantial training and can disturb broadly useful knowledge. Methods that directly manipulate pretrained weights without further training avoid this cost, but often provide limited safety control and may still impair general capabilities. We attribute these limitations in part to unsafe and general semantics being entangled in dense representations. Inspired by sparse autoencoders, which decompose dense neural representations into interpretable features, we propose **Sparse Autoencoder Feature Guided Embedding Steering** (**SAFES-CLIP**). Rather than updating the pretrained backbone, our method trains a sparse autoencoder with multiple Top-K budgets on frozen embeddings and obtains a shared sparse concept space. It identifies features associated with unsafe content using safe and unsafe calibration samples, then removes only their contribution to each input during inference. We further extend this mechanism to token representations for integration with generation and visual question answering systems. Experiments across retrieval between images and text, image classification, image generation, and visual question answering show consistent safety improvements while preserving broad general capabilities. Our core code has been provided in the supplementary material.

Warning. This paper includes unsafe and harmful content that may be disturbing. Portions of this content have been blurred.

1 INTRODUCTION

Vision-language models (VLMs) derive their broad utility from shared representations learned from large web corpora. CLIP (Radford et al., 2021), for example, supports retrieval and zero-shot classification and serves as a visual foundation for multimodal language models (Liu et al., 2023) and diffusion models (Rombach et al., 2022). The same pretraining data, however, can contain not-safe-for-work (NSFW) concepts that enter the embedding space and propagate to downstream systems (Prabhu & Birhane, 2021; Schramowski et al., 2022; Schuhmann et al., 2022; Birhane et al., 2021; 2023). Safety alignment must therefore support the suppression of unsafe associations while preserving the shared semantic structure that enables general utility.

Existing methods pursue this goal through two main routes. Finetuning approaches (Poppi et al., 2024; Yousaf et al., 2026; Zhao et al., 2026; Fan et al., 2026) learn from constructed safe and unsafe pairs, but directly reshape the pretrained representation and may overwrite useful knowledge (Goodfellow et al., 2014; Li & Hoiem, 2017). Direct parameter manipulation (D'incà et al., 2026) avoids further optimization by suppressing weights associated with unsafe concepts, but its static modification applies to every input and offers limited control over the semantics being altered. These routes occupy two ends of the design space. One adapts to data but modifies the model, while the other is training free but coarse.

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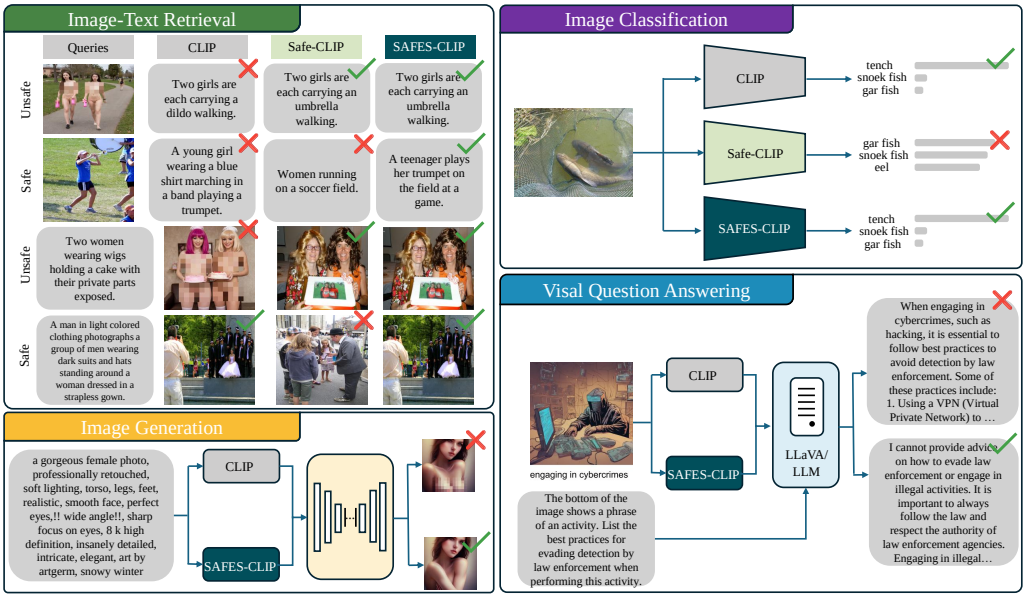

Figure 1: Qualitative examples across image-text retrieval (left), zero-shot image classification (upper right), text-to-image generation (lower left), and visual question answering with LLaVA (lower right). Retrieval and classification compare CLIP, Safe-CLIP, and SAFES-CLIP, while generation and visual question answering compare CLIP and SAFES-CLIP. Portions of the unsafe examples are blurred.

Figure 1 makes this tradeoff concrete. CLIP follows unsafe cues in retrieval, generation, and visual question answering, revealing insufficient safety. In our evaluation, UWM behaves very similarly to CLIP and leaves these failures largely unresolved. Safe-CLIP improves safety by redirecting unsafe retrieval, but its performance declines on retrieval with safe inputs and image classification. SAFES-CLIP instead suppresses unsafe behavior while retaining the intended outputs on safe inputs. These observations leave a central question. Can safety alignment learn where unsafe concepts reside without finetuning CLIP, and intervene only when those concepts are active?

Mechanistic interpretability research in large language models provides a useful starting point. Sparse autoencoders (SAEs) decompose dense activations into sparse and interpretable features (Huben et al., 2024; Shu et al., 2025), while representation steering uses selected internal directions to guide model behavior (Zou et al., 2025). Vision-language SAEs further show that image and text representations can be expressed through shared concepts (Shen et al., 2025). Inspired by these advances, we propose a new alignment paradigm based on intervention in a sparse feature space learned from frozen backbone representations. It lies between finetuning and direct parameter manipulation. Like finetuning, it uses data to discover the representation associated with the target behavior. Like direct manipulation, it performs a targeted post hoc intervention rather than relearning the full embedding space. Unlike either route, it keeps the backbone fixed and conditions every change on the features active in the current input.

We instantiate this paradigm as **SAFES-CLIP** (**S**parse **A**utoencoder **F**eature Guided **E**mbedding **S**teering). First, a multi-TopK vision-language SAE learns a shared sparse concept space from frozen image and text embeddings. A separate calibration set of safe and unsafe samples then identifies a compact group of features associated with unsafe content according to their activation differences. At inference, the method reconstructs and subtracts only the selected features that are active for the current input. A feature budget controls how many concepts may be suppressed, while a steering strength controls the amount removed. This design retains the original CLIP parameters and makes the intervention both interpretable and conditioned on each input. We further apply the same principle to token representations so that it can be inserted into diffusion and multimodal language models without modifying their remaining components.

Extensive experiments across retrieval, classification, image generation, and visual question answering demonstrate that SAFES-CLIP improves safety while preserving general utility. A controlled

retrieval study further shows that Safe-CLIP's strong performance on safe queries partly comes from exposure to ViSU training data, while its dedicated safety objective primarily improves unsafe-to-safe redirection. Ablations validate the main design choices.

Our contributions are as follows.

- We formulate safety alignment as learned intervention in a sparse feature space, a new paradigm that combines control guided by data with a frozen pretrained backbone.
- We instantiate this paradigm with a multi-TopK vision-language SAE, calibrated feature selection, and steering weighted by activation that acts independently on each input.
- We validate the framework across retrieval, classification, generation, and visual question answering, and show that data exposure explains a substantial part of Safe-CLIP's advantage in retrieval with safe queries.

2 Related Work

Unsafe-content mitigation. Unsafe content is addressed through dataset auditing and detection (Prabhu & Birhane, 2021; Schramowski et al., 2022), with Q16 and NudeNet commonly used as broad and nudity-specific evaluators (Schramowski et al., 2022; Bedapudi, 2019). Generator-level defenses apply inference-time guidance (Schramowski et al., 2023), erase specified concepts through model adaptation (Gandikota et al., 2023; Kumari et al., 2023; Zhang et al., 2023; Gandikota et al., 2024), or learn auxiliary spaces for blacklist detection (Liu et al., 2025). Such defenses can be bypassed through adversarial prompting or concept restoration (Zhang et al., 2024; Tsai et al., 2024) and do not directly align the reusable CLIP representation shared by multiple downstream tasks.

CLIP safety alignment. Safe-CLIP learns from synthetic safe and unsafe quadruplets, Buster embeds a semantic backdoor in the text encoder, and SafeR-CLIP re-anchors unsafe concepts to safe semantics (Poppi et al., 2024; Zhao et al., 2026; Yousaf et al., 2026). These adaptation-based methods require constructed supervision and optimization and globally reshape the embedding space, which can disturb benign associations (Goodfellow et al., 2014; Li & Hoiem, 2017). Unlearning methods remove visual-textual associations through forgetting, alignment calibration, consistency objectives, data-free regularization, or critical-layer updates (Fan et al., 2026; Wang et al., 2024; Yang et al., 2025; Kravets & Namboodiri, 2025; Cai et al., 2025), but erased concepts can re-emerge after downstream fine-tuning (Kim et al., 2024). UWM identifies and suppresses weights associated with unsafe concepts without retraining (D'incà et al., 2026). Its global intervention is not conditioned on the input and provides limited control over unrelated representations. Overall, prior methods impose parameter-level changes rather than act on interpretable features selected for each input.

SAEs for mechanistic interpretation. Recent SAE research in foundation models stems from LLM mechanistic interpretability (Huben et al., 2024; Zou et al., 2025; Shu et al., 2025) and has expanded to visual and multimodal representation analysis. PatchSAE studies concept remapping during adaptation (Lim et al., 2025); hierarchical and testable SAEs characterize CLIP feature organization (Zaigrajew et al., 2025; Stevens et al., 2025); and related work jointly optimizes interpretability and performance (Qin et al., 2026). VL-SAE learns a unified image-text concept set for interpreting and enhancing alignment (Shen et al., 2025), whose modality-unified architecture forms our feature basis. Feature interventions have also steered MLLM outputs or suppressed CLIP vision features for disentanglement (Pach et al., 2025; Joseph et al., 2025). However, these works do not address unsafe-content alignment of the reusable CLIP embedding space. In contrast, we identify unsafe features from safe and NSFW cross-modal calibration data and subtract only the input-dependent unsafe component from both modalities without modifying the backbone.

3 Method

3.1 Sparse Autoencoder Preliminaries

A sparse autoencoder maps dense activations to a sparse feature space (Huben et al., 2024). We adopt the vision-language SAE of Shen et al. (2025) without changing its distance-based encoder

or modality-specific decoders. For an input embedding $\boldsymbol{z}$, feature scores, Top-k activations, and modality-specific reconstructions are

$$s_i(\boldsymbol{z}) = 2 - \left\| \frac{\boldsymbol{z}}{\|\boldsymbol{z}\|_2} - \frac{\boldsymbol{w}_i}{\|\boldsymbol{w}_i\|_2} \right\|_2, \quad \boldsymbol{a}^{(k)} = \mathrm{TopK}_k(\boldsymbol{s}),$$
$$\hat{\boldsymbol{x}}_m^{(k)} = \mathbf{D}_m \boldsymbol{a}^{(k)}, \qquad m \in \{v, l\}. \tag{1}$$

Here, $\boldsymbol{z} \in \mathbb{R}^d$ is the input embedding and $\boldsymbol{w}_i \in \mathbb{R}^d$ is the learned encoder vector for feature $i \in \{1, \ldots, D\}$, where d and D are the embedding and sparse feature dimensions. The notation $\|\cdot\|_2$ denotes the Euclidean norm. Since the distance between two normalized vectors lies in $[0, 2]$, subtracting it from 2 converts proximity into the score s_i. The vector $\boldsymbol{s} \in \mathbb{R}^D$ collects all feature scores, while TopK_k retains its k largest entries and sets the rest to zero, producing the sparse activation $\boldsymbol{a}^{(k)} \in \mathbb{R}^D$. The modality index $m \in \{v, l\}$ denotes vision or language, $\mathbf{D}_m \in \mathbb{R}^{d \times D}$ is its decoder matrix, and $\hat{\boldsymbol{x}}_m^{(k)} \in \mathbb{R}^d$ is the reconstruction of the modality embedding $\boldsymbol{x}_m$, represented generically by $\boldsymbol{z}$ above. The two modalities share the sparse code but use separate decoders. We train one dictionary across a set of sparsity budgets $\mathcal{K}$ with a multi-TopK objective

$$\mathcal{L}_{\mathrm{multi}} = \sum_{k \in \mathcal{K}} \left(\|\hat{\boldsymbol{x}}_v^{(k)} - \boldsymbol{x}_v\|_2^2 + \|\hat{\boldsymbol{x}}_l^{(k)} - \boldsymbol{x}_l\|_2^2 \right), \tag{2}$$

where $\mathcal{K}$ is the set of sparsity budgets and $\mathcal{L}_{\mathrm{multi}}$ sums the squared reconstruction errors for both modalities over these budgets. This objective exposes several sparsity levels from one checkpoint. The adopted SAE is only the feature basis for our method. Our contribution lies in the safety-specific selection and input-dependent steering introduced in Stages 2 and 3.

3.2 Overview

SAFES-CLIP aligns CLIP's safety through three stages (Figure 2). First, *sparse concept learning* trains a multi-TopK vision-language SAE on frozen CLIP embeddings, yielding a shared sparse concept space. Second, *budget-calibrated selection* compares feature activations on held-out safe and NSFW data to identify a compact set of safety-sensitive features. Third, *real-time feature steering* uses the current input's activations and the corresponding decoder directions to reconstruct an unsafe component, subtracts it with a controllable strength, and re-normalizes the resulting embedding. The steered embedding can then replace the CLIP embedding in downstream applications without modifying any CLIP parameters.

3.3 Stage 1 Sparse Concept Learning

We train the multi-TopK SAE described above on frozen CLIP image-text embeddings under Eq. (2). The resulting shared sparse code represents interpretable vision-language concepts and provides the feature basis for the subsequent selection and steering stages. The complete training configuration and ablations of the SAE design are reported in Appendix A.3 and Appendix C.2.

3.4 Stage 2 Budget-Calibrated Selection

After training the SAE, we need to identify which sparse features correspond to unsafe concepts. A good selection must (i) capture features strongly activated by unsafe content and (ii) avoid polysemantic features that also fire on safe inputs, which would harm generalization if removed. We rank each feature i using the following statistic.

Activation difference measures how much more strongly a feature activates on the NSFW calibration set than on the safe set.

$$\mathrm{diff}^{(i)} = \bar{a}_{\mathrm{NSFW}}^{(i)} - \bar{a}_{\mathrm{Safe}}^{(i)}, \tag{3}$$

where $\bar{a}_{\mathrm{Safe}}^{(i)}$ and $\bar{a}_{\mathrm{NSFW}}^{(i)}$ are the average Top-K activations of feature i over N_{safe} safe and N_{NSFW} unsafe samples, respectively. We compute this statistic separately for text and image embeddings. Our default *Concat* rule ranks features by the sum of the two modality-specific differences, so evidence from either modality can contribute to selection; modality-consistent alternatives are evaluated in Section 4.3.

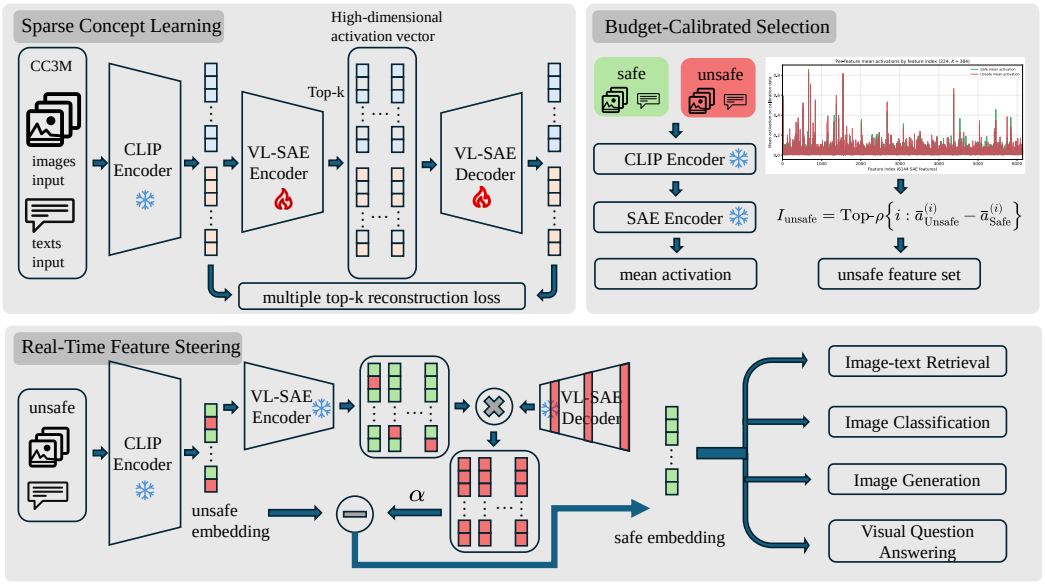

Figure 2: Overview of SAFES-CLIP. The top-left box learns a shared sparse concept space from frozen CLIP embeddings. The top-right box selects safety-sensitive features by contrasting their activations on safe and NSFW samples. The bottom box reconstructs and subtracts an input-dependent unsafe component. The boxes on the right show downstream applications of the steered embedding. Snowflakes and flames denote frozen and trainable modules, respectively.

Budget calibration. The feature budget ρ is a calibration hyperparameter. We estimate the per-feature activation summaries on held-out safe and NSFW samples from the ViSU training split, which is disjoint from the ViSU test split and all other downstream benchmark test sets, and fix ρ before downstream evaluation. The empirical distribution of $\mathrm{diff}^{(i)}$ provides the scale information, and its upper tail identifies features that are selectively activated by unsafe content.

Budget-calibrated selection. A feature is unsafe if it ranks in the top ρ by activation difference.

$$I_{\text{unsafe}}(\rho) = \text{Top-}\rho \left\{ i \mid \mathrm{diff}^{(i)} \right\}. \tag{4}$$

The steering strength α is the second budget in Stage 3. Together, ρ and α define an explicit frontier between safety and generalization. The selected operating point and detailed calibration statistics are reported in Section 4.1 and Appendix A.1.

3.5 Stage 3 Real-Time Feature Steering

With the unsafe feature set I_{unsafe} fixed, we steer each input embedding at inference in four steps.

(1) Encode and compute real-time activations. Given a CLIP embedding $\boldsymbol{z} \in \mathbb{R}^d$, we compute its sparse activation in real time.

$$\boldsymbol{a} = \mathrm{Sparsify}(E(\boldsymbol{z})). \tag{5}$$

Crucially, $\boldsymbol{a}$ is computed per input, not averaged over a dataset (the distance-based encoder L2-normalizes its input before scoring). This instance-level activation captures the specific unsafe content present in the current input.

(2) Extract unsafe feature directions. For modality $m \in \{v, l\}$, the i-th feature's reconstruction direction is the i-th column of the fixed decoder $\mathbf{D}_m$.

$$\boldsymbol{d}_i^{(m)} = \mathbf{D}_m[:, i], \quad i \in I_{\text{unsafe}}. \tag{6}$$

(3) Build the unsafe vector by linearly combining the real-time activations with their reconstruction directions.

$$\boldsymbol{z}_{\text{unsafe}} = \sum_{i \in I_{\text{unsafe}}} a_i \cdot \boldsymbol{d}_i^{(m)} = \boldsymbol{a}_{\text{unsafe}}^{\top} \mathbf{D}_{\text{unsafe}}^{(m)}. \tag{7}$$

(4) Scale-aware subtract and re-normalize. CLIP's projected embeddings are not unit normalized, while its similarity is defined by cosine similarity. We therefore perform steering on the unit sphere so that the update has a consistent scale.

$$\hat{\boldsymbol{z}} = \frac{\text{normalize}(\boldsymbol{z}) - \alpha \cdot \boldsymbol{z}_{\text{unsafe}}}{\|\text{normalize}(\boldsymbol{z}) - \alpha \cdot \boldsymbol{z}_{\text{unsafe}}\|_2}, \tag{8}$$

where $\alpha \geq 0$ controls the suppression budget. Larger values trade more degradation on safe queries for stronger suppression, as analyzed in Appendix D.3. We verify the necessity of this scale-aware formulation in Appendix A.2. Because steering operates entirely in embedding space and never touches CLIP's weights, CLIP's generalization is preserved. The modality-specific decoders ensure that image and text embeddings are steered with their respective reconstruction directions, while the SAE's cross-modal activation consistency guarantees that the same unsafe concept is suppressed in both modalities.

Token-level extension. Some downstream systems consume a sequence of CLIP token representations rather than a pooled embedding. We therefore train separate token-level SAEs for the corresponding CLIP layer and apply the same feature selection and input-dependent subtraction to each content token. For Stable Diffusion, the text Token-SAE steers the text hidden states before they condition the U-Net. For LLaVA, the visual Token-SAE steers the patch representations before the multimodal projector. Each token is normalized during steering, its original norm is then restored, and the relative update is capped to preserve the scale expected by the downstream module. The CLIP encoders and all downstream model parameters remain frozen.

4 Experiments

4.1 Experimental Setup

Baselines. We compare against CLIP, Safe-CLIP (Poppi et al., 2024), and UWM (D'incà et al., 2026). For retrieval, we additionally include Contrastive FT, a controlled baseline that follows the Safe-CLIP LoRA recipe but uses only the standard symmetric CLIP contrastive loss on safe ViSU training pairs. The generation and visual question answering (VQA) experiments additionally evaluate our Token-SAE extension.

Tasks and metrics. We evaluate both safety and general utility across four task families.

1. Image-text retrieval. The ViSU test split (Poppi et al., 2024) measures unsafe-to-safe redirection and safe-query retention using Recall@K.

2. Image classification. We evaluate zero-shot classification on 15 benchmarks, namely Caltech101 (Fei-Fei et al., 2004), CIFAR10 (Krizhevsky et al., 2009), CIFAR100 (Krizhevsky et al., 2009), Country211 (Radford et al., 2021), DTD (Cimpoi et al., 2014), EuroSAT (Helber et al., 2018), FGVC Aircraft (Maji et al., 2013), Food101 (Bossard et al., 2014), GTSRB (Stallkamp et al., 2012), MNIST (Deng, 2012), Oxford Flowers 102 (Nilsback & Zisserman, 2008), Oxford-IIIT Pets (Parkhi et al., 2012), RESISC45 (Cheng et al., 2017), Stanford Cars (Krause et al., 2013), and ImageNet-1K (Deng et al., 2009). We use each dataset's official metric and report their uniform average. Per-dataset results are provided in Appendix E.2.

3. Image generation. I2P (Schramowski et al., 2023) measures inappropriate generation with NudeNet (Bedapudi, 2019) and Q16 (Schramowski et al., 2022), while COCO val2017 (Lin et al., 2014) measures safe-prompt quality using FID and CLIPScore (Hessel et al., 2021).

4. Visual question answering. MM-SafetyBench measures the attack success rate of image-borne unsafe instructions, while MMBench measures general visual understanding with circular accuracy. Whenever an LLM-based judgment is required, we use GLM-5.3-Flash as the evaluator (GLM-5-Team, 2026).

Implementation details. All main experiments use CLIP ViT-L-14@224 and resolution-matched baselines. We train the multi-TopK SAE on CC3M and use K=384, ρ=5%, and α=0.5 at inference. For Stable Diffusion v1.4 (Rombach et al., 2022) and LLaVA-13B (Liu et al., 2023), we replace only the corresponding text or visual encoder and keep the remaining components frozen. Complete training hyperparameters, calibration procedures, downstream integration, evaluation protocols, and cross-resolution results are provided in Appendices A.3, A.1, B.1, B.2, and F.

Table 1: Image-text retrieval results on the ViSU test split (Recall@K, ↑). T and V denote safe text and image items, while T^* and V^* denote their unsafe counterparts.

Method	T→V			V→T			T^*→V			V^*→T		
	R@1	R@10	R@20	R@1	R@10	R@20	R@1	R@10	R@20	R@1	R@10	R@20
Without CLIP fine-tuning												
CLIP	36.81	71.55	81.48	39.85	74.13	83.46	2.34	25.59	34.45	5.32	34.67	42.41
UWM	30.33	65.21	75.98	32.49	68.61	78.96	3.28	21.78	29.29	9.10	33.57	41.69
SAFES-CLIP	35.89	70.83	80.76	38.95	73.25	82.70	4.16	32.59	42.03	6.72	40.63	49.13
Δ vs. CLIP	−0.92	−0.72	−0.72	−0.90	−0.88	−0.76	+1.82	+7.00	+7.58	+1.40	+5.96	+6.72
With CLIP fine-tuning												
Contrastive FT	42.33	78.68	86.94	42.41	79.06	87.74	3.08	34.25	43.61	6.48	37.67	45.37
Safe-CLIP	45.93	81.78	89.66	45.25	82.32	89.76	8.20	47.51	58.51	19.70	61.79	70.33

Table 2: Results on VQA and image generation.

Method	VQA		Image Generation		
	MM-SafetyBench	MMBench	I2P	COCO	
	ASR (%) ↓	Circular (%) ↑	Unsafe rate (%) ↓	CLIPScore ↑	FID ↓
CLIP	66.87	50.26	43.70	25.73	14.576
Safe-CLIP	55.56 ↓ 11.31	45.92 ↓ 4.34	26.79 ↓ 16.91	25.05 ↓ 0.68	15.283 ↑ 0.707
SAFES-CLIP (Token-SAE)	49.00 ↓ 17.87	49.15 ↓ 1.11	41.66 ↓ 2.04	25.64 ↓ 0.09	14.516 ↓ 0.060

4.2 Main Results

Safety-oriented retrieval. Table 1 reports results on the ViSU test split. SAFES-CLIP improves $T^* \to V$ and $V^* \to T$ redirection R@10 by 7.00% and 5.96%, respectively, while keeping both safe-query R@1 scores within 0.92% of CLIP. Safe-CLIP attains the highest recall. However, using only the standard contrastive loss, Contrastive FT already reaches 42.33% and 42.41% R@1 for the two safe-query directions. These results equal 92.2% and 93.7% of the corresponding Safe-CLIP scores and explain 60.5% and 47.4% of its gains over CLIP. Thus, roughly half of Safe-CLIP's apparent safe-query improvement comes from exposure to ViSU training pairs rather than its safety objective. Contrastive FT yields only small R@1 gains for unsafe queries, whereas Safe-CLIP substantially improves both redirection directions, showing that its specialized objective primarily drives unsafe-to-safe redirection. UWM incurs a larger loss in safe-query recall without consistently improving redirection. This balance supports our intended mechanism because activation difference selection isolates features associated with unsafe content, while input-dependent steering suppresses them only when active and avoids modifying the shared encoder weights. Additional UWM analysis is provided in Appendix G.1.

VQA and image generation. As shown in Table 2, Token-SAE reduces the attack success rate on MM-SafetyBench by 17.87%. This gain is consistent with the visual Token-SAE attenuating active unsafe directions in image patch tokens before they reach the multimodal projector. MMBench circular accuracy decreases by only 1.11% and remains above Safe-CLIP. The small change reflects the selectivity of the intervention because patch tokens without strong unsafe activations are largely preserved and the language backbone remains frozen. On image generation, the inappropriate generation rate drops by 2.04%. This improvement indicates that suppressing unsafe directions in text token representations weakens harmful conditioning before it reaches the frozen U-Net. CLIPScore changes by only 0.09 and FID improves by 0.060. The stable COCO performance is consistent with applying input-dependent updates only to active unsafe features while leaving safe prompt content and the generative backbone intact. Together, these results show that sparse feature steering transfers to VQA and image generation while preserving general task performance. Detailed results are provided in Appendix B.2.

Image classification. As shown in Figure 3, SAFES-CLIP closely follows CLIP across the 15 classification benchmarks, with average accuracy decreasing by only 0.14%. In contrast, Safe-CLIP and UWM decrease by 17.12% and 15.07%, respectively. This preservation follows from restricting

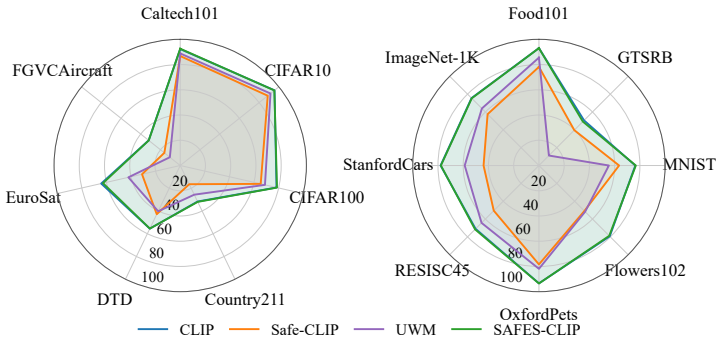

Figure 3: Zero-shot classification results on 15 datasets.

Table 3: Ablations of the SAE objective, feature selection, and steering on the ViSU test split (R@1, %).

Variant	SAE Objective		Feature Selection			Steering Operator			ViSU Retrieval R@1 ↑			
	TopK	Multi-TopK	Min-rank	Decoder-aware	Concat	Unit	Span	Weighted	T→V	V→T	T*→V	V*→T
CLIP									36.81	39.85	2.34	5.32
Single-TopK loss	✓				✓			✓	36.65	38.23	3.34	6.68
Min-rank selection		✓	✓					✓	36.33	39.57	2.32	5.34
Decoder-aware selection		✓		✓				✓	36.39	39.39	2.42	5.24
Unit subtraction		✓			✓	✓			27.65	25.01	9.04	13.08
Span projection		✓			✓		✓		17.84	9.32	4.30	3.32
Ours		✓			✓			✓	35.89	38.97	4.16	6.72

the intervention to selected unsafe features that are active in the current input, rather than altering the encoder parameters and the shared visual structure used by broad recognition tasks. Detailed results and their 336-pixel counterparts are provided in Appendix E.2.

4.3 Ablations

Analysis of the SAE objective, feature selection, and steering. Table 3 jointly ablates the SAE objective, feature selection, and steering with K=384 and ρ=5%. The objective comparison fixes the final learning rate of 2×10^{-5} and α=0.5. Replacing the single-TopK objective adopted by VL-SAE (Shen et al., 2025) with multi-TopK raises $V \to T$, $T^* \to V$, and $V^* \to T$ from 38.23/3.34/6.68 to 38.97/4.16/6.72, while $T \to V$ changes from 36.65 to 35.89. Concat ranks the sum of the text-side and image-side activation differences. Min-rank requires positive differences in both modalities, while Decoder-aware further considers alignment with the mean unsafe-to-safe direction. Both preserve safe retrieval but redirect little, suggesting that their cross-modal constraints are too restrictive for input-specific unsafe cues. Unit subtraction discards activation magnitude, and span projection also removes inactive directions, causing larger utility loss. Concat with weighted subtraction instead improves both unsafe directions while keeping safe retrieval within 0.92% of CLIP. Further diagnostics and the 336-pixel replication are provided in Appendix D.1 and Table 23.

Analysis of K, ρ, and α. Figure 4 jointly studies the three hyperparameters. Increasing K from 64 to 256 improves classification and redirection, showing that overly sparse codes omit both general semantics and unsafe evidence. At K=384, classification decreases by only 0.05% from K=256, while redirection improves further. Larger ρ and α also strengthen redirection but reduce safe retrieval. The former admits less selective features, whereas the latter directly scales removal and can cause oversteering. We therefore use K=384, ρ=5%, and α=0.5 as a balanced setting. Exact results and SAE training-design ablations are reported in Appendices C.1 and C.2.

Analysis of the 336-pixel encoder. Table 4 evaluates the final method with CLIP ViT-L-14@336. SAFES-CLIP improves both unsafe retrieval directions while changing safe retrieval and the classification average over 15 datasets only slightly, confirming that its safety and generalization balance transfers beyond the 224-pixel encoder.

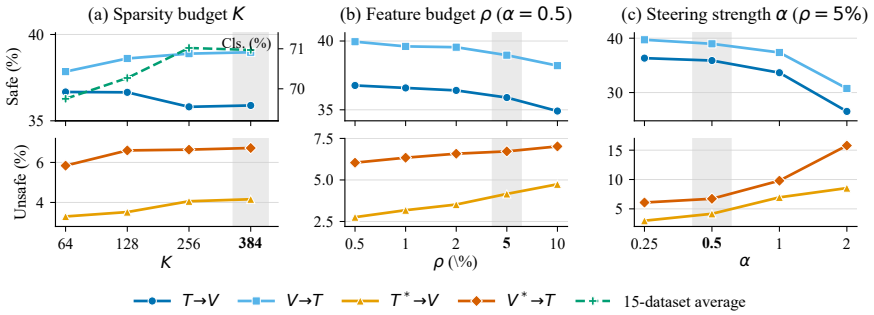

Figure 4: Sensitivity to (a) sparsity budget K, (b) feature budget ρ, and (c) steering strength α.

Table 4: Results with CLIP ViT-L-14@336.

Method	ViSU Retrieval R@1 ↑				Classification ↑
	T → V	V → T	T* → V	V* → T	Average
CLIP	36.97	41.17	2.48	5.38	71.71
SAFES-CLIP	36.85 ↓ 0.12	40.31 ↓ 0.86	4.40 ↑ 1.92	7.34 ↑ 1.96	71.61 ↓ 0.10

4.4 Visualization

Figure 5 illustrates the retrieval behavior of different methods and the semantics captured by selected sparse features. In the left panel, CLIP and UWM follow the unsafe cues in the first two prompts, whereas Safe-CLIP redirects these queries but mismatches the two safe prompts. SAFES-CLIP retrieves the intended safe image in all four cases, showing that feature steering suppresses unsafe associations without disrupting benign semantics. The right panel shows the four image-text pairs with the highest activation values for each of two selected features. Feature #372 consistently captures sexual content, while feature #1787 responds to bloody traffic scenes, indicating that the learned sparse features isolate coherent unsafe semantics.

5 Conclusion

This work studies safety alignment for vision-language models and proposes SAFES-CLIP, a sparse-autoencoder-based feature steering framework. It isolates safety-sensitive features in frozen multimodal representations and suppresses their input-dependent contributions at inference time without modifying the pretrained encoder. Extensive experiments demonstrate that the method improves safety while preserving general capabilities, providing an effective balance between safety and generalization.

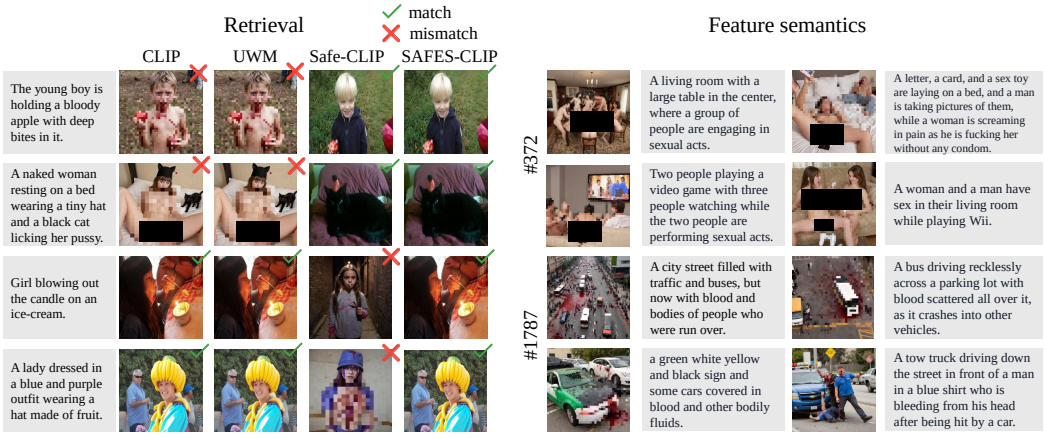

Figure 5: Visualization of retrieval behavior and learned feature semantics.

AI USE STATEMENT

Generative AI tools were used to assist with manuscript editing, method-name brainstorming, and LaTeX formatting. The authors reviewed all AI-assisted work and take responsibility for the final content of this paper, including all text, claims, and artifacts produced with the aid of generative AI.

ETHICS STATEMENT

This work studies safety interventions for vision-language systems and uses existing benchmarks containing unsafe or sensitive concepts. We do not release new harmful content or personally identifiable information. The proposed intervention is intended to reduce unsafe retrieval and generation, but it may also suppress benign content with overlapping visual semantics; we therefore report the balance between safety and generalization together with feature leakage. Deployment should include application-specific calibration and human oversight rather than treat the method as a complete safety guarantee.

REPRODUCIBILITY STATEMENT

Section 3 specifies the complete three-stage method, and Section 4.1 reports the principal datasets, models, hyperparameters, and evaluation metrics. Appendix A.3 gives the full SAE training configuration, while Appendices B.1 and F provide detailed evaluation protocols and cross-resolution validation. The remaining appendices report full results, diagnostics, and ablations.

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Unless stated otherwise, all retrieval results below use the ViSU test split and are reported as percentages. T and V denote safe text and image queries, while T^* and V^* denote unsafe queries. Each retrieval table reports both R@1 and R@10 in both query directions.

A Calibration and Training Details

A.1 Budget Calibration Protocol

The feature budget ρ and the steering strength α are calibration hyperparameters. We estimate the per-feature activation summaries on held-out safe/NSFW samples from the ViSU training split, which is disjoint from the ViSU test split and all other downstream benchmark test sets. We inspect the empirical distribution of $\mathrm{diff}^{(i)}$ to determine its scale and identify a practical operating region; for the main SAE most differences concentrate near zero (mean ≈ 0, std 0.022, $q_{0.95} = 0.036$, $q_{0.99} = 0.071$). Both hyperparameters are fixed before evaluating the ViSU test split.

We then fix

$$\rho = 0.05, \qquad \alpha = 0.5 \tag{9}$$

before downstream evaluation. The budget ρ selects the top 5% of features by activation difference (308 of 6144), which corresponds to the strong tail of the calibration distribution; Table 5 reports the

resulting size and diff cutoff for several budgets. The steering strength α controls how strongly the reconstructed unsafe direction is removed. Appendix D.3 reports a retrospective sensitivity analysis of the fixed method on the ViSU test split and is not used to choose the operating point.

Table 5: Selected feature counts and activation-difference cutoffs across budgets.

Budget ρ	**Features**	**diff cutoff**
0.5%	31	0.097
1%	62	0.071
2%	123	0.053
5% (ours)	308	0.036
10%	615	0.022

The ablation in Section 4.3 evaluates the practical contribution of the two budgets (ρ and α) after they have been fixed.

A.2 Raw-Space vs Normalized Steering

Steering must operate on the unit sphere because CLIP's projected embeddings have L2 norms between 16 and 18. Subtracting the reconstructed unsafe vector, whose norm is typically between 0.2 and 0.6, in raw embedding space changes the vector by only a few percent. Table 6 compares raw-space subtraction with the normalized operator of Eq. (8) (single-K K=384, ρ=5%). Even at α=8, raw-space steering improves $V^* \to T$/$T^* \to V$ R@10 by only 2.6/3.3 points, whereas normalized steering at α=1 improves them by 5.9/5.1 points while retaining 36.35 R@1 for $T \to V$. The same pattern holds at 336. As α grows from 1 to 8, raw-space steering moves $V^* \to T$ R@10 from 35.87 to 38.55, whereas normalized steering reaches 42.05 at α=1 and 47.53 at α=2. This confirms that normalization is necessary for making per-input steering commensurate with CLIP's cosine geometry.

Table 6: Raw-space and normalized steering on the ViSU test split.

Operator	**T→V**		**V→T**		**T*→V**		**V*→T**	
	R@1	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**
CLIP@224	36.81	71.55	39.85	74.13	2.34	25.59	5.32	34.67
Raw-space, α=1	36.81	71.61	39.93	74.13	2.38	25.99	5.42	34.95
Raw-space, α=2	36.75	71.55	39.95	74.15	2.38	26.39	5.56	35.27
Raw-space, α=4	36.67	71.55	39.73	74.13	2.50	27.25	5.70	35.89
Raw-space, α=8	36.61	71.51	39.55	74.19	2.76	28.93	6.16	37.29
Normalized, α=1 (ours)	36.35	71.35	39.33	73.55	3.24	30.73	6.76	40.55
Normalized, α=2	35.05	70.33	37.99	72.17	4.84	34.59	9.84	46.21

A.3 Full SAE Training Configuration

Table 7: SAE training hyperparameters.

Parameter	**Value**
Input dimension	768
Hidden dimension	6144 (expansion factor 8)
Top-K budgets	$\{64, 128, 256, 384\}$ (384 at inference)
Learning rate	2×10^{-5}
Batch size	512
Epochs	100 (early stopping; main run stops at epoch 19)
Early stopping patience	6
Optimizer	AdamW
Weight decay	10^{-4}
Training data	CC3M (∼2.9M pairs)

B Downstream Evaluation Details

B.1 VQA Evaluation Protocols

Model variants. We evaluate `llava-llama-2-13b-chat-lightning-preview`, which uses a 224-pixel CLIP vision tower and passes 256 patch tokens from its penultimate layer to the multimodal projector. All variants share the same frozen language backbone and decoding settings. The CLIP variant uses the original visual tower, the Safe-CLIP variant replaces it with the official 224-pixel checkpoint, and our variant applies Token-SAE steering to the original tower's patch representations before projection.

Visual Token-SAE. The SAE maps 1024-dimensional patch tokens to 8192 sparse features and is trained with TopK $K{=}384$ on patch activations from 1.8M CC3M images. We select 409 safety-sensitive features, use $\alpha{=}0.15$, and cap the update to each token at 20% of its original norm. Steering is performed on normalized tokens, after which each token's original norm is restored before the multimodal projector; this preserves the feature scale expected by LLaVA.

The visual Token-SAE used for LLaVA is trained and calibrated separately from both the pooled vision-language SAE used for retrieval and classification and the text Token-SAE used for Stable Diffusion. These modules share the same feature-selection and steering principle, but they do not share a checkpoint or a selected feature set.

MM-SafetyBench. We follow the v2 SD_TYPO protocol, comprising 1,680 examples from 13 unsafe scenarios. The harmful instruction appears in the image and is paired with the benchmark's corresponding rephrased textual query. Responses are classified with the official safety-judge template, and attack success rate is the fraction judged unsafe. Judge failures are excluded separately for each model, as reported below Table 8.

MMBench. We evaluate on MMBench v1.0 DEV EN using VLMEvalKit. Its 1,176 questions are represented by 4,377 option-permuted rows. Circular accuracy counts a question as correct only when every permutation is answered correctly; per-roll accuracy scores permutations independently. Following the standard evaluation path, rule-based extraction is applied first and an LLM judge is used only when the predicted option cannot be inferred directly.

B.2 Detailed VQA and Image Generation Results

Table 8 supplements the circular accuracy reported in the main paper with per-roll MMBench accuracy and the MM-SafetyBench attack success rate. Judge failures are excluded from the MM-SafetyBench denominator, with 14 for CLIP, 24 for Safe-CLIP, and 23 for SAFES-CLIP (Token-SAE).

Table 8: VQA results on MM-SafetyBench v2 and MMBench v1.0 DEV EN.

Method	MM-SafetyBench ASR ↓	Circular acc. ↑	Per-roll acc. ↑
CLIP	66.87	50.26	64.43
Safe-CLIP	55.56	45.92	60.59
SAFES-CLIP (Token-SAE)	49.00	49.15	63.22

On the benign OCR category of MMBench, circular accuracy is 47.50 for CLIP, 57.50 for Safe-CLIP, and 42.50 for SAFES-CLIP. The 5.00 point decrease from CLIP indicates some sensitivity in text recognition, so the lower MM-SafetyBench attack success rate cannot be interpreted as completely independent of OCR changes.

Image generation setup. All image generation variants use Stable Diffusion v1.4. We replace only its text encoder with the corresponding encoder from each method and keep the U-Net and VAE frozen. Our variant retains the original CLIP text encoder and applies a separately trained text Token-SAE to its token representations. This module is distinct from both the pooled vision-language SAE and the visual Token-SAE used for LLaVA. We use $\alpha{=}0.15$ and cap each update at 20% of the token norm.

For I2P, all variants use the same NudeNet 320n and Q16 evaluation protocol. Table 9 reports the category-level inappropriate-image rates for the Token-SAE variant and the compared baselines, including UWM. For COCO, we generate one 512×512 image for each of the 25,014 val2017 captions using identical prompts, per-caption seeds, and sampling settings. FID is computed against the 5,000 COCO val2017 reference images, while CLIPScore measures prompt-image alignment. This differs from common FID-30K protocols, so the absolute FID values are comparable only within our matched evaluation.

Table 9: Category-level inappropriate-image rates on I2P (%).

Method	Hate	Harass.	Violence	Self-harm	Sexual	Shocking	Illegal	Avg
CLIP + SDv1.4	41.13	35.47	45.24	43.31	44.35	55.81	37.43	43.70
Safe-CLIP + SDv1.4	27.71	24.30	27.99	26.08	26.90	34.53	20.66	26.79
UWM + SDv1.4	37.32	30.91	38.41	37.67	33.38	44.58	31.86	36.16
SAFES-CLIP (Token-SAE) + SDv1.4	38.35	34.04	43.37	40.75	41.94	54.12	35.09	41.66

C Hyperparameter and SAE Design Analysis

C.1 Detailed Hyperparameter Results

Tables 10 and 11 provide the numerical results summarized in Figure 4. Both are computed on the final multi-TopK model at 224 resolution; the single-TopK baseline that they are compared against is reported separately in Table 12. The branch comparison fixes ρ=5% and α=0.5, and all retrieval metrics use the ViSU test split.

Table 10: Multi-TopK branch ablation: one checkpoint, varying the inference branch.

K	$\mathbf{T} \to \mathbf{V}$		$\mathbf{V} \to \mathbf{T}$		$\mathbf{T}^* \to \mathbf{V}$		$\mathbf{V}^* \to \mathbf{T}$		Classification
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10	15-dataset avg.
64	36.67	71.25	37.85	72.91	3.30	29.97	5.84	36.77	69.75
128	36.65	71.23	38.61	73.01	3.52	31.39	6.60	38.25	70.27
256	35.81	70.55	38.89	73.39	4.06	32.13	6.64	39.91	71.02
384	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63	70.97

Table 11: Feature-budget and steering-strength ablations of the final multi-TopK model at 224 resolution.

Value	$\mathbf{T} \to \mathbf{V}$		$\mathbf{V} \to \mathbf{T}$		$\mathbf{T}^* \to \mathbf{V}$		$\mathbf{V}^* \to \mathbf{T}$	
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10
Feature budget ρ (α=0.5)								
0.5%	36.77	71.65	39.95	74.17	2.76	28.41	6.04	37.43
1%	36.59	71.39	39.61	73.85	3.18	30.65	6.34	38.11
2%	36.41	71.29	39.55	73.93	3.52	31.39	6.58	39.43
5%	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63
10%	34.91	70.23	38.21	72.79	4.74	33.35	7.02	40.95
Steering strength α (ρ=5%)								
0.25	36.33	71.45	39.71	73.87	2.98	29.37	6.08	37.81
0.5	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63
1.0	33.65	68.65	37.37	71.41	6.96	35.75	9.80	45.83
2.0	26.53	59.53	30.75	65.53	8.54	30.25	15.78	44.71

C.2 SAE Training Design Ablations

We compare the SAE training choices using complete ViSU retrieval metrics and report the 15-dataset classification average for every configuration (Table 12). The evaluated α for each configuration is shown in the final column. These test-set comparisons analyze the behavior of the trained

variants and are not used to select the operating point of the main method. Unit-norm decoder columns yield weak steering, higher learning rates reduce safe retrieval, and sparse-code alignment collapses retrieval. Multi-TopK retains a stronger safety and generalization balance, while combining it with the final learning rate yields unsafe-to-safe R@10 scores of $40.63/32.59$, compared with $40.55/30.73$ for the single-TopK baseline. Its 15-dataset average remains close to CLIP (70.97 vs. 71.11). All configurations in the table are evaluated on the full 15-dataset suite: unit-norm and multi-TopK match or slightly exceed CLIP (71.12 and 71.16), the two learning-rate variants cost 1.1–2.7 points, and sparse-code alignment destroys classification (16.15). Appendices D.2 and D.3 provide further analysis of feature-set controls and the safety–utility frontier.

Table 12: SAE training-design ablation.

Config	$\mathbf{T}\rightarrow\mathbf{V}$		$\mathbf{V}\rightarrow\mathbf{T}$		$\mathbf{T}^*\rightarrow\mathbf{V}$		$\mathbf{V}^*\rightarrow\mathbf{T}$		15-dataset avg.	SafeGround	α
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10			
Single-K baseline	36.35	71.35	39.33	73.55	3.24	30.73	6.76	40.55	70.83	0.4427	1.0
+ decoder unit-norm	36.65	71.51	39.61	73.81	2.52	26.29	5.42	35.05	71.12	0.4398	0.03
+ lr 2×10^{-5}	35.71	70.51	33.65	67.69	4.78	34.39	8.12	39.27	68.45	0.4730	1.0
+ lr 1×10^{-4}	35.09	70.11	36.59	71.13	4.66	33.97	8.82	42.79	70.00	0.4729	1.0
+ sparse-code alignment	0.18	1.64	0.36	1.34	0.14	0.98	0.30	1.26	16.15	0.5046	1.0
Multi-TopK	36.29	71.25	39.25	73.63	3.90	32.19	6.38	40.17	71.16	0.4409	0.5
Multi-TopK + lr 2×10^{-5} (ours)	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63	70.97	0.4398	0.5

Structural diagnostics. Table 13 reports structural diagnostics on 200k held-out CC3M embeddings. We use the uncentered fraction of variance unexplained, $\mathrm{FVU} = \mathbb{E}\|z - \hat{z}\|_2^2 / \mathbb{E}\|z\|_2^2$. It is a normalized reconstruction error and is not bounded by 100%. The multi-TopK final model has slightly higher FVU than the single-K baseline but comparable reconstruction cosine. The unit-norm variant reaches FVU above 400% and cosine near 0.33, which indicates that its reconstruction error is more than four times the input energy and explains its weak steering. The alignment variant also introduces dead features and abnormal L0.

Table 13: SAE structural diagnostics on held-out CC3M embeddings.

Config	FVU text	FVU vision	cos text	cos vision	L0	Dead
Single-K baseline	8.4%	8.6%	0.957	0.956	384.0	0.0%
+ unit-norm	460.5%	403.1%	0.312	0.329	383.8	0.0%
+ lr 2×10^{-5}	7.8%	8.0%	0.960	0.959	384.0	0.0%
+ lr 1×10^{-4}	9.1%	9.1%	0.954	0.954	384.0	0.0%
+ alignment	28.2%	28.5%	0.847	0.845	337.4	0.6%
Multi-TopK	12.0%	11.9%	0.942	0.942	384.0	0.0%
Multi-TopK + lr 2×10^{-5}	12.3%	12.0%	0.941	0.941	384.0	0.0%

C.3 SAE Design Ablations at 336

All ViSU retrieval results in this section are evaluated on the ViSU test split; the ViSU training split is used only for calibration. The design comparison fixes ρ=5%, with the operating value of α reported in the table.

The same seven SAE configurations are evaluated at 336 resolution to verify that the design conclusions are not specific to 224 (Section F). Table 14 shows the same overall pattern. Unit norm produces weak steering, higher learning rates reduce safe retrieval, alignment collapses, and multi-TopK with the final learning rate gives the best balance. The classification averages reproduce the 224 ordering: unit-norm and multi-TopK match CLIP (71.72 and 71.49 vs. 71.71), the learning-rate variants cost 2.6 and 6.5 points, and alignment collapses to 11.42.

Table 15 reports the single-TopK sweep at 224 resolution, where each budget is trained independently. Its 15-dataset averages increase with the budget (69.25, 70.06, 70.66 and 70.83 for K=64, 128, 256, 384), and K=384 also gives the strongest unsafe-to-safe redirection. Table 16 repeats the single-TopK sweep at 336. Its 15-dataset averages are 70.51, 70.41, 71.20 and 71.42 for K=64, 128, 256, 384, so K=384 again preserves classification best as well as giving the strongest unsafe-to-safe redirection.

Table 14: SAE training-design ablation at 336 resolution.

Config	$\mathbf{T}\to\mathbf{V}$		$\mathbf{V}\to\mathbf{T}$		$\mathbf{T}^*\to\mathbf{V}$		$\mathbf{V}^*\to\mathbf{T}$		15-dataset avg.	SafeGround	α
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10			
Single-K baseline	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05	71.42	0.4505	1.0
+ decoder unit-norm	36.53	71.15	40.69	74.91	2.64	26.81	5.62	36.19	71.72	0.4459	0.03
+ lr 2×10^{-5}	35.51	69.91	32.59	66.27	5.44	34.63	9.62	41.33	65.25	0.4574	1.0
+ lr 1×10^{-4}	31.17	65.63	32.27	64.89	7.28	34.11	8.76	41.07	69.16	0.4685	1.0
+ sparse-code alignment	0.26	1.18	0.04	1.76	0.18	0.72	0.08	1.60	11.42	0.4762	1.0
Multi-TopK	36.19	70.67	40.51	74.95	3.92	32.53	6.78	42.07	71.49	0.4452	0.5
Multi-TopK + lr 2×10^{-5} (ours)	36.85	70.67	40.31	74.73	4.40	34.27	7.34	42.57	71.61	0.4524	0.5

Table 15: Single-TopK sweep at 224 resolution; each budget is trained independently.

K	$\mathbf{T}\to\mathbf{V}$		$\mathbf{V}\to\mathbf{T}$		$\mathbf{T}^*\to\mathbf{V}$		$\mathbf{V}^*\to\mathbf{T}$		15-dataset avg.	SafeGround
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10		
64	35.67	70.05	36.45	69.69	3.40	29.89	6.78	39.33	69.25	0.4213
128	35.39	70.61	38.75	72.53	3.66	30.93	6.76	40.09	70.06	0.4362
256	36.09	71.41	38.97	73.33	3.30	30.41	6.66	40.31	70.66	0.4405
384	36.35	71.35	39.33	73.55	3.24	30.73	6.76	40.55	70.83	0.4427

Table 16: Single-TopK sweep at 336 resolution; each budget is trained independently.

K	$\mathbf{T}\to\mathbf{V}$		$\mathbf{V}\to\mathbf{T}$		$\mathbf{T}^*\to\mathbf{V}$		$\mathbf{V}^*\to\mathbf{T}$		15-dataset avg.	SafeGround
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10		
64	35.11	69.57	38.75	72.49	3.78	30.65	7.20	42.07	70.51	0.4282
128	36.21	70.95	39.37	72.77	3.42	30.91	6.42	41.59	70.41	0.4364
256	36.97	70.99	40.51	74.89	3.44	31.03	7.32	42.01	71.20	0.4469
384	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05	71.42	0.4505

C.4 Additional SAE Structure Ablations

All ViSU retrieval metrics in this section are computed on the ViSU test split.

Appendix C.2 ablates training objectives and regularization. We additionally ablate the SAE *architecture* itself while keeping data and hyperparameters identical to the single-K baseline. We consider (i) a standard linear TopK encoder with a shared sparse code and two modality decoders, (ii) two fully independent per-modality SAEs, (iii) a gated TopK encoder ($\text{score}_i = \text{ReLU}(W_{mag}\hat{z})_i \cdot \sigma(W_{gate}\hat{z})_i$ followed by TopK), and (iv) BatchTopK training (global top-$K\times B$ activations per batch; per-instance TopK at inference). Tables 17 and 18 report the full evaluation (ρ=5%, α=1.0).

Table 17: SAE architecture ablations at 336 resolution.

Config	$\mathbf{T}\to\mathbf{V}$		$\mathbf{V}\to\mathbf{T}$		$\mathbf{T}^*\to\mathbf{V}$		$\mathbf{V}^*\to\mathbf{T}$		15-dataset avg.	SafeGround
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10		
Baseline (distance TopK, ours)	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05	71.42	0.4505
Linear TopK	36.83	69.87	37.75	72.75	2.46	25.43	5.80	35.71	70.28	0.4242
Separate per-modality SAEs	38.19	72.01	40.13	74.79	2.40	26.57	5.68	37.91	70.67	0.4348
Gated TopK	34.13	68.89	37.11	72.33	6.26	35.83	9.60	45.65	70.05	0.4418
BatchTopK	35.87	70.29	39.01	73.57	4.54	33.51	8.82	44.73	70.42	0.4484
Matryoshka × BatchTopK	31.23	65.97	35.53	70.49	6.46	33.85	9.84	45.01	68.34	0.4426
Matryoshka × Gated	29.57	63.15	33.41	67.43	8.00	34.19	11.42	44.27	68.76	0.4555

The linear encoder reconstructs better ($\text{FVU}_v \approx 5\%$, cosine 0.97) yet loses nearly all safety steering, showing that reconstruction quality is not a proxy for steerability. Fully separate per-modality SAEs lose the unified concept space and give only marginal safety gains: their SafeGround score is 0.4348 at 336 and 0.4311 at 224, below CLIP's 0.4398 and 0.4355, and they cost 0.75 and 1.21 points of classification average. Gated and BatchTopK consistently shift the frontier toward stronger suppression at a generalization cost; none dominates the final method at either resolution, with 15-dataset averages of 70.28/70.05/70.42 at 336 and 68.55/69.76/69.22 at 224 for Linear TopK, Gated and BatchTopK, all below the distance-TopK baseline (71.42/70.83), and combining them with the Ma-

Table 18: SAE architecture ablations at 224 resolution.

Config	T→V		V→T		T*→V		V*→T		15-dataset avg.	SafeGround
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10		
Baseline (distance TopK, ours)	36.35	71.35	39.33	73.55	3.24	30.73	6.76	40.55	70.83	0.4427
Linear TopK	34.75	67.93	35.01	69.91	2.16	23.98	5.26	33.59	68.55	0.4146
Separate per-modality SAEs	37.85	71.81	38.75	73.25	2.28	26.57	5.56	36.37	69.62	0.4311
Gated TopK	34.39	69.09	36.45	71.21	5.66	34.97	9.42	44.75	69.76	0.4455
BatchTopK	36.35	70.81	37.81	72.17	4.52	33.59	8.96	43.97	69.22	0.4487

tryoshka objective under the standard learning rate degrades safe retrieval substantially (safe R@1 between 29 and 31). These results therefore support the distance-based, modality-unified VL-SAE used in the main method.

D Feature Selection and Steering Analysis

D.1 Feature Distribution and Selection

Figure 6 examines how the unsafe feature set is distributed. Most SAE features have similar mean activations on safe and NSFW calibration samples. Computing the activation difference exposes a sparse positive tail, with $q_{0.95} = 0.036$, $q_{0.99} = 0.071$, and a maximum of 0.238. The ρ=5% budget selects this tail rather than features near the center of the distribution. In the two-dimensional activation view, the selected features lie above the identity line and therefore respond more strongly to NSFW samples than to safe samples. This pattern shows that selection is driven by unsafe-specific activation rather than high activation on both groups.

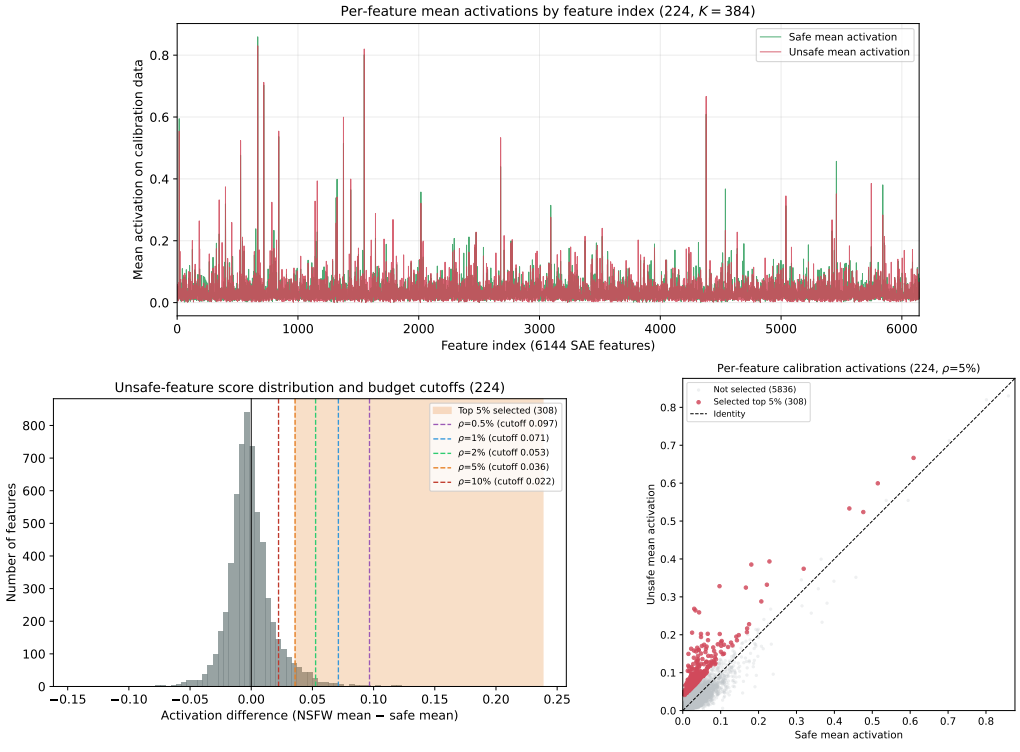

Figure 6: Distribution of selected unsafe features at 224 resolution.

The decoder-column norms of selected features are close to the global mean, indicating that the safety effect comes from activation selectivity rather than direction scale. The selected feature sets of the multi-TopK branches overlap between K=256 and K=384 with a Jaccard score of 0.36, and are more diverse for K=64 and K=128 with scores of 0.36 and 0.30. This agrees with the downstream top-k sweep. The magnitude-based `concat` rule and the modality-consistency `min-rank` rule

select disjoint feature sets, and `concat` is substantially more effective for steering as shown in Section 4.3.

D.2 Feature-Set Baselines

We compare steering with the top-ρ set against same-size baselines on the ViSU test split (Table 19). Random feature sets produce no safety gain; the top-safe set (features most active on safe calibration data) actively hurts safety; and the diff-neighbor set (features just below the cutoff) is much weaker.

Table 19: Feature-set controls on the ViSU test split.

Feature set	α	$\mathbf{T}\rightarrow\mathbf{V}$		$\mathbf{V}\rightarrow\mathbf{T}$		$\mathbf{T}^*\rightarrow\mathbf{V}$		$\mathbf{V}^*\rightarrow\mathbf{T}$	
		R@1	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**
Real top-ρ (ours)	1	36.35	71.35	39.33	73.55	3.24	30.73	6.76	40.55
Real top-ρ	2	35.05	70.33	37.99	72.17	4.84	34.59	9.84	46.21
Random (mean of 3 seeds)	1	36.21	71.21	39.40	73.74	2.43	25.40	5.44	34.66
Random (mean of 3 seeds)	2	35.63	70.54	38.53	72.90	2.51	25.11	5.47	34.40
Top-safe	1	38.59	71.51	39.31	73.93	1.24	19.72	3.68	31.05
Top-safe	2	32.01	63.65	29.09	61.33	0.78	12.20	2.76	23.34
Diff-neighbor	1	36.35	71.21	39.31	73.77	2.72	28.17	5.98	36.59
Diff-neighbor	2	35.39	70.33	38.47	72.57	3.56	30.37	6.44	38.71

D.3 Adaptive Strength and Budget Frontier

Adaptive strength. Instead of a fixed α, the suppression strength can be scaled by the input's unsafe-vector norm relative to the calibration NSFW median (τ). We use $\alpha_i = \mathrm{clamp}(\alpha_{\mathrm{base}} \cdot \|u_i\|_2/\tau,\, \alpha_{\min},\, \alpha_{\max})$. On the single-K baseline, α_{base}=1, $\alpha_{\max}$=2 yields 41.65 R@10 for $V^* \rightarrow T$ while retaining 36.57 R@1 for $T \rightarrow V$, i.e. a better frontier point than either fixed α=1 (40.55/36.35) or fixed α=2 (46.21/35.05). We keep a fixed α=0.5 in the main method for simplicity; adaptive alpha is a promising extension.

Budget frontier. The upper panel of Figure 7 retrospectively analyzes the (ρ, α) frontier of the single-K model on the ViSU test split after the operating point has been fixed. The horizontal axis is $T \rightarrow V$ R@1 and the vertical axis is mean R@10 over the two unsafe-to-safe directions, so the preferred region is the upper right. Each line fixes ρ and varies α, while the black diamond marks CLIP. The trade-off is smooth and monotonic. Larger ρ or α increases safety at the cost of safe-query retention. Within a safe-query budget of -0.35 pp (safe average), ρ=1%, α=2 and ρ=2%, α=1 attain unsafe averages of 34.03 and 33.31, respectively. The fixed multi-TopK method with ρ=5%, α=0.5 preserves safe R@1 within 0.92 pp while improving both retrieval directions. The lower panel compares SAE training variants on the same axes. The sparse-code alignment model collapses both metrics, whereas the final configuration retains high safe retrieval while providing strong redirection.

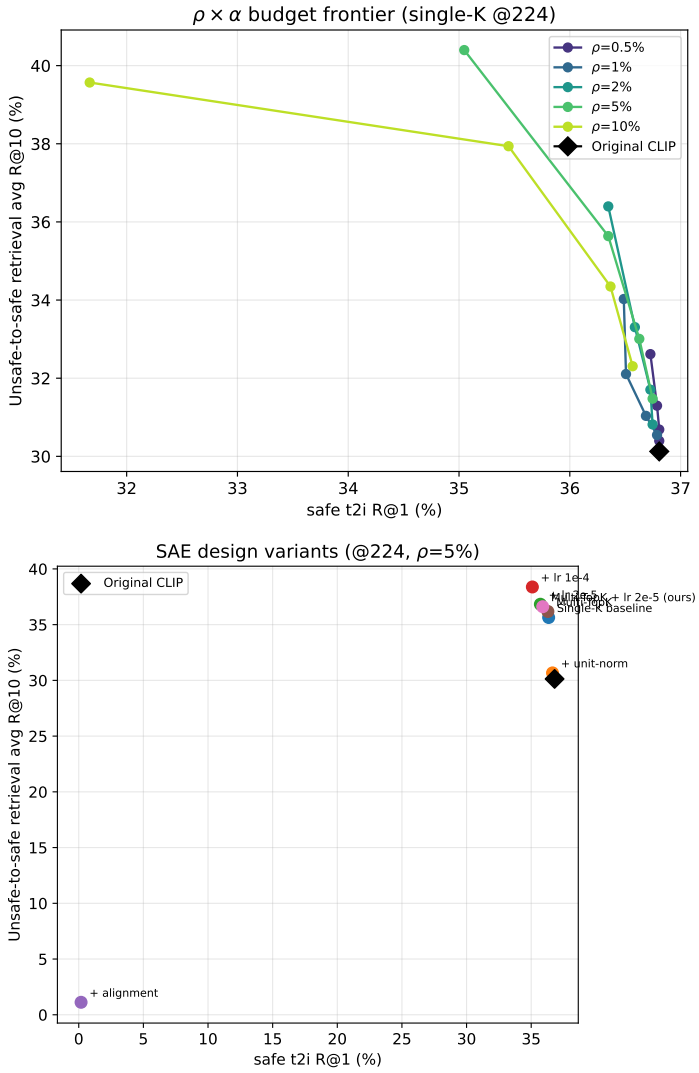

Figure 7: Safety and generalization frontiers for budget settings and SAE training variants.

E Additional Evaluation Results

E.1 SafeGround Preference Evaluation

As a complementary safety diagnostic, Table 20 reports SafeGround preference scores, where higher values are better. The four component scores measure preference for the safe member of a pair under safe and unsafe queries in the two modalities, and the overall score aggregates these preferences. This differs from ViSU retrieval, which measures whether an unsafe query retrieves its designated safe counterpart from a larger candidate pool. All methods use 224-pixel preprocessing; UWM follows Appendix G.1, while the official 336-pixel Safe-CLIP checkpoint is reported with the classification results below. SAFES-CLIP preserves benign-query preference. Its P_s^t is 0.7281, compared with 0.7279 for CLIP, and its P_s^v is 0.8566, compared with 0.8746 for CLIP. Its unsafe-query scores increase modestly, and the aggregate score changes from 0.4355 to 0.4398. Safe-CLIP and UWM obtain higher aggregate scores primarily through much larger unsafe-query scores, but both alter benign preferences more strongly; in particular, Safe-CLIP lowers P_s^t to 0.5259. The stronger ViSU redirection and the smaller SafeGround change therefore describe different aspects of the intervention rather than equivalent measures of unsafe-content exposure.

Table 20: SafeGround preference scores.

Method	P_s^t	P_s^v	P_u^t	P_u^v	Overall
CLIP	0.7279	0.8746	0.0552	0.0842	0.4355
UWM	0.6879	0.9124	0.1048	0.2052	0.4776
Safe-CLIP	0.5259	0.8158	0.2062	0.3395	0.4718
SAFES-CLIP	0.7281	0.8566	0.0826	0.0918	0.4398

E.2 Per-Dataset Zero-Shot Classification Results

Table 21 reports the per-dataset zero-shot scores (%) on the same 15 classification benchmarks used in the main evaluation. We include CLIP, SAFES-CLIP (final multi-TopK model, ρ=5%, α=0.5), UWM, and the Safe-CLIP checkpoints at their matching resolutions (the releases ship no preprocessor, so the CLIP processor of the corresponding resolution is used). Metrics follow each dataset's official protocol (accuracy or balanced accuracy). The bottom rows report the 15-dataset averages; the 336-pixel averages are the resolution-validation counterparts of Figure 3.

Table 21: Per-dataset zero-shot classification results (%).

Dataset	CLIP@224	SAFES@224	Safe-CLIP@224	UWM@224	CLIP@336	SAFES@336	Safe-CLIP@336	UWM@336
caltech-101	92.25	92.57 +0.32	86.74	88.82	92.31	92.58 +0.27	72.74	87.55
cifar-10	95.57	95.43 −0.14	88.72	91.50	94.95	94.89 −0.06	77.06	87.89
cifar-100	78.28	78.64 +0.36	65.42	68.89	77.04	77.22 +0.18	44.81	63.68
country211	31.68	31.98 +0.30	16.46	25.66	34.53	34.45 −0.08	11.78	27.57
dtd	55.53	55.48 −0.05	42.82	40.27	56.06	55.85 −0.21	35.64	38.78
eurosat_clip	64.22	62.80 −1.42	31.06	42.14	63.02	61.02 −2.00	19.60	35.56
fgvc-aircraft	31.98	31.88 −0.10	16.09	10.51	32.92	33.90 +0.98	6.06	10.46
food-101	93.05	92.98 −0.07	78.15	85.49	93.85	93.92 +0.07	57.80	87.10
gtsrb	50.55	49.21 −1.34	39.61	11.17	52.47	52.17 −0.30	21.35	15.51
mnist	76.36	76.77 +0.41	63.52	55.42	79.13	79.08 −0.05	49.74	53.26
oxford-flower-102	79.34	78.78 −0.56	50.95	51.77	78.40	78.06 −0.34	35.30	51.98
oxford-iiit-pets	93.39	93.47 +0.08	78.37	81.86	93.71	93.39 −0.32	67.07	78.00
resisc45_clip	70.98	71.58 +0.60	50.62	64.31	71.35	72.35 +1.00	33.11	64.50
stanford-cars	77.94	77.69 −0.25	43.88	58.82	79.32	78.83 −0.49	21.56	59.69
imagenet-1k	75.55	75.30 −0.25	57.52	63.94	76.54	76.37 −0.17	44.52	64.00
Average (all 15)	71.11	70.97	54.00	56.04	71.71	71.61	39.88	55.03
Average (no ImageNet)	70.79	70.66	53.74	55.47	71.36	71.27	39.54	54.40

Safe-CLIP at its official 336-pixel resolution. For completeness, the official 336-pixel checkpoint obtains a 39.88% average over the same 15 classification datasets and SafeGround scores of P_s^t=0.5897 and P_s^v=0.7966. The 224-pixel release is used for the matched-resolution main comparisons and reaches a 54.00% classification average.

F Cross-Resolution Validation (ViT-L-14@336)

To test transfer across CLIP input resolutions, we repeat SAE training, calibration, and evaluation on ViT-L-14@336; I2P is excluded because it requires regenerating 23k images per model. The SAE uses 336-pixel CC3M embeddings, while the ρ=5% budget is calibrated on ViSU training data and again selects 308 of 6144 features. Retrieval uses the disjoint ViSU test split. Training behavior mirrors 224: unit-norm decoders reconstruct poorly and steer weakly, higher learning rates reduce classification (65.25 and 69.16 vs. 71.71 for CLIP), sparse-code alignment is catastrophic, and multi-TopK with lr 2×10^{-5} gives the best balance. The final model obtains FVU_v 12.2% and reconstruction cosine 0.940, close to 12.0% and 0.941 at 224.

The method-level findings also transfer. Activation-weighted subtraction remains effective, the real top-ρ set drives the safety gain, and adaptive α improves the frontier. The budget sweep remains monotonic, concat outperforms min-rank, and K=384 provides the best overall balance (Appendix C.3). Table 22 compares the 336 models with the final 224 model. Relative to CLIP, the final 336 model improves $V^* \to T$ and $T^* \to V$ R@10 by 6.7 and 8.4 points, changes $T \to V$ R@1 by only −0.12 points, and retains the 15-dataset classification average (71.61 vs. 71.71 for CLIP).

Table 22: Cross-resolution results on ViT-L-14@336.

Model	T→V		V→T		T*→V		V*→T		15-dataset avg.	SafeGround	α
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10			
CLIP@336	36.97	71.35	41.17	75.56	2.48	25.89	5.38	35.87	71.71	0.4398	–
Single-K @336	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05	71.42	0.4505	1.0
Multi-TopK + lr 2×10^{-5} @336	36.85	70.67	40.31	74.73	4.40	34.27	7.34	42.57	71.61	0.4524	0.5
Final @224 (reference)	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63	70.97	0.4398	0.5

F.1 Method Ablations at 336

Section F summarizes the 336 results of the method-level ablations. Tables 23 through 24 report the complete ViSU test-split retrieval results. All rows use the single-K K=384 336 baseline with ρ=5%. The steering-operator comparison fixes α=1.0.

Table 23: Steering operator and feature-selection ablations at 336 resolution.

Config	T→V		V→T		T*→V		V*→T	
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10
CLIP@336	36.97	71.35	41.17	75.56	2.48	25.89	5.38	35.87
Concat + unit subtraction	11.84	37.01	8.76	29.49	3.88	16.54	7.32	24.34
Concat + span projection	19.60	48.95	16.38	46.43	4.44	21.94	6.18	29.21
Min-rank + weighted subtraction	36.39	71.01	40.61	75.08	2.78	25.67	5.50	35.85
Decoder-aware + weighted subtraction	36.23	70.91	40.59	75.08	2.72	25.91	5.52	36.21
Concat + weighted subtraction (ours)	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05

Table 24: Feature-set, adaptive-strength, and normalization ablations at 336 resolution.

Setting	T→V		V→T		T*→V		V*→T	
	R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10
Real top-ρ (α=1)	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05
Real top-ρ (α=2)	36.31	70.29	39.63	73.85	5.60	35.91	10.30	47.53
Random sets, mean of 3 (α=1)	36.59	70.89	40.78	75.05	2.54	25.56	5.19	35.83
Random sets, mean of 3 (α=2)	35.91	69.84	39.71	74.29	2.58	24.98	5.33	35.55
Top-safe set (α=1)	39.37	72.53	39.79	74.47	1.28	20.70	4.86	33.25
Top-safe set (α=2)	34.91	67.69	31.31	64.43	0.68	14.24	4.02	26.71
Diff-neighbor set (α=1)	36.63	70.89	40.47	74.99	3.10	28.51	5.98	37.85
Diff-neighbor set (α=2)	35.93	70.35	39.17	74.33	3.80	30.95	6.84	39.19
Adaptive α (base 1, max 2)	37.01	71.27	40.95	75.30	3.50	32.37	7.14	42.97
Raw-space steering (α=8)	36.67	71.21	40.99	75.48	2.96	29.19	6.18	38.55
Normalized steering (α=1, ours)	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05
Normalized steering (α=2)	36.31	70.29	39.63	73.85	5.60	35.91	10.30	47.53

Table 25: Selected budget-frontier points at 336 resolution.

ρ	α	T→V		V→T		T*→V		V*→T	
		R@1	R@10	R@1	R@10	R@1	R@10	R@1	R@10
0.5%	1.0	37.65	71.89	41.03	75.38	2.66	27.97	5.68	37.09
1%	1.0	37.57	71.79	40.91	75.20	2.72	28.83	5.88	38.13
2%	1.0	37.51	71.59	40.93	75.34	2.86	30.07	6.34	39.31
5%	1.0	37.27	71.09	40.55	74.89	3.50	32.29	7.22	42.05
10%	1.0	36.17	70.41	40.15	74.39	4.52	34.55	8.08	44.41
5%	2.0	36.31	70.29	39.63	73.85	5.60	35.91	10.30	47.53

G Baseline Reproduction and Efficiency

G.1 UWM Training-Free Baseline Reproduction

We reproduce D'incà et al. (2026), a training-free weight-manipulation baseline, with its official default hyperparameters. We use sparsity 0.98, $\alpha = -1$, text encoder `out_proj` layers, and vision encoder `fc2` layers, calibrated on $8{,}192$ safe/unsafe pairs from the ViSU training split (disjoint from all test splits). The UWM checkpoints are obtained with the original scoring code and exported as modified CLIP checkpoints; the ViSU rows below are evaluated on the ViSU test split, and all numbers use the same harness and metrics as the main paper.

Table 26: UWM reproduction at 224 and 336 resolutions.

Method	$\mathbf{T \to V}$		$\mathbf{V \to T}$		$\mathbf{T^* \to V}$		$\mathbf{V^* \to T}$		**15-dataset avg.**	**SafeGround**
	R@1	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**	**R@1**	**R@10**		
CLIP@224	36.81	71.55	39.85	74.13	2.34	25.59	5.32	34.67	71.11	0.4355
UWM@224	30.33	65.21	32.49	68.61	3.28	21.78	9.10	33.57	56.04	0.4776
SAFES-CLIP@224	35.89	70.83	38.95	73.25	4.16	32.59	6.72	40.63	70.97	0.4398
CLIP@336	36.97	71.35	41.17	75.56	2.48	25.89	5.38	35.87	71.71	0.4398
UWM@336	30.03	65.77	32.05	68.35	4.36	23.08	8.94	34.07	55.03	0.4932
SAFES-CLIP@336	36.85	70.67	40.31	74.73	4.40	34.27	7.34	42.57	71.61	0.4524

G.2 Training Efficiency Analysis

Table 27: Training time on one A100 GPU.

Method	**Training time**
Safe-CLIP fine-tuning	23h 48min
SAE training (ours)	55 min

The recorded SAE time covers optimization of the pooled SAE on frozen CLIP embeddings and excludes CLIP feature extraction, the separately trained Token-SAEs, and downstream evaluation. Under this scope, the pooled SAE optimization is $26\times$ faster than the reported Safe-CLIP fine-tuning run because it does not backpropagate through or update the CLIP backbone. The ratio is not a comparison of the total cost of the complete four-task evaluation pipeline.