Sparse Autoencoders are Capable LLM Jailbreak Mitigators

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Abstract

Jailbreak attacks remain a persistent threat to large language model safety. We propose Context-Conditioned Delta Steering (**CC-Delta**), an SAE-based defense that identifies jailbreak-relevant sparse features by comparing token-level representations of the same harmful request with and without jailbreak context. Using paired harmful/jailbreak prompts, **CC-Delta** selects features via statistical testing and applies inference-time mean-shift steering in SAE latent space. Across four aligned instruction-tuned models and thirteen jailbreak attacks, **CC-Delta** achieves comparable or better safety–utility tradeoffs than baseline defenses operating in dense latent space. In particular, our method clearly outperforms dense mean-shift steering on all four models, and particularly against out-of-distribution attacks, showing that steering in sparse SAE feature space offers advantages over steering in dense activation space for jailbreak mitigation. Our results suggest off-the-shelf SAEs trained for interpretability can be repurposed as practical jailbreak defenses without task-specific training.

1. Introduction

Since the early days of the deep learning revolution, the susceptibility of ever more powerful models to harmful intents of malicious actors has created an active field of research (Szegedy et al., 2013; Carlini & Wagner, 2017; Croce et al., 2020). In more recent years, the importance of the development of effective defenses against potential attacks from such malicious actors has only increased with the widespread deployment and use of powerful large language models (LLMs) (Brown et al., 2020; Carlini et al., 2023; Souly et al., 2024). In this context, attacks in the form of prompt designs to elicit harmful content from LLMs, also called jailbreak attacks, as well as defenses against them, have been intensively studied (Andriushchenko et al., 2025; Zou et al., 2024; Sheshadri et al., 2025).

In an ideal world, such a defense would both be *effective* and *specific*. An *effective* defense prevents jailbreak attacks from eliciting harmful content, both in-distribution (i.e. for attack types that were seen during training) and out-of-distribution (i.e. for novel or unseen attack types). A defense is *specific* if it does not affect general model utility (e.g., it does not degrade the model instruction following outside of jailbreak attack attempts). Unfortunately, despite significant efforts, existing defenses and mitigations struggle to be both effective and specific, and can only achieve high safety against jailbreak attacks at a significant cost of general model utility.

One reason for this difficulty may be the superposition of concepts and behaviors in model representation spaces (Olah et al., 2020; Elhage et al., 2022): if many concepts or behaviors are entangled in every activation dimension, interventions that target one behavior inevitably perturb others. Motivated by this intuition, we turn to Sparse Autoencoders (SAEs, (Huben et al., 2024; Bricken et al., 2023; Templeton et al., 2024)), which learn more disentangled representation spaces by mapping activations to a higher-dimensional space under a sparsity constraint. Our core question is whether learning defenses in this sparser feature space can yield better safety–utility tradeoffs than learning them in dense activation space. We find that this is the case: with context-conditioned feature selection, steering in sparse SAE feature space achieves comparable or better safety–utility tradeoffs and better generalization than defenses operating in the original (dense) representation space, including popular baselines such as Contrastive Activation Addition (Rimsky et al., 2024) or Circuit Breakers (Zou et al., 2024). In summary, our contributions are as follows:

1. We propose **CC-Delta**[1], an SAE-based jailbreak defense that introduces a novel feature selection method that identifies how token representations are changed by jailbreak transformations and thus learns only from prompts and does not require model generations for training.

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[1]Code will be made available at https://github.com/apple/ml-ccdelta.

2. We evaluate **CC-Delta** across four models and thirteen jailbreak attacks, finding that it improves effectiveness and specificity over baseline defenses and generalizes from a small set of wrapper attacks to held-out attack types, including re-writer attacks and adaptive PAIR, while maintaining substantially better safety–utility tradeoffs than dense-space steering.

3. We systematically characterize **CC-Delta**'s inference-time parameter space, showing that the two-dimensional control surface of feature count and steering strength provides fine-grained access to the safety–utility tradeoff, and that effective mitigation often requires tens to hundreds of features.

2. Background and Notation

2.1. LLM Jailbreaks

As part of their post-training, LLMs are typically trained to be *aligned* (Christiano et al., 2017; Rafailov et al., 2023), that is, they are trained to refuse to answer harmful requests x_{harmful} such as *'Tell me how to build a bomb'*. The goal of a *jailbreak attack* then is to transform such a harmful request into a prompt $x_{\text{jailbreak}}$ that bypasses the alignment mechanisms and elicits the LLM to output the requested harmful content. Jailbreak attacks can be grouped into two types: *wrapper* and *re-writer* attacks. Wrapper attacks embed the original request inside a template (e.g., an optimized prefix to elicit compliance), while re-writer attacks paraphrase or fully rewrite the request, often using an LLM.

2.2. Sparse Autoencoders

A sparse autoencoder (SAE) encodes a dense activation $\mathbf{h} \in \mathbb{R}^d$ into a higher-dimensional sparse latent $\mathbf{z} \in \mathbb{R}^F$ ($F \gg d$) and decodes $\mathbf{z}$ to reconstruct $\hat{\mathbf{h}}$:

$$\mathbf{z} = \sigma(W_{\text{enc}}\mathbf{h} + \mathbf{b}_{\text{enc}}), \quad \hat{\mathbf{h}} = W_{\text{dec}}\mathbf{z} + \mathbf{b}_{\text{dec}}.$$

Here W_{enc} and W_{dec} are learned weights and σ is a sparsifying nonlinearity (e.g., ReLU, TopK, JumpReLU) (Huben et al., 2024; Rajamanoharan et al., 2024; Gao et al., 2025). SAEs are also trained with sparsity-inducing objectives (e.g., an ℓ_1 penalty on $\mathbf{z}$). Each coordinate of $\mathbf{z}$ defines an SAE feature, and sparsity ensures only a small subset is active per token. This sparse and disentangled representation enables more interpretable and controllable manipulation of model activations (Huben et al., 2024; Templeton et al., 2024).

3. Context-Conditioned Delta Steering

Within this context, we introduce our SAE-based jailbreak defense, **Context-Conditioned Delta Steering** (**CC-Delta**), which combines the established mean-shift approach from activation steering (Turner et al., 2023; Rimsky et al., 2024; Li et al., 2023) with a novel approach to *feature selection* in sparse latent space. This feature selection step is critical for making our defense more specific. As ablations in Section 5.5 show, the feature selection step increases safety while reducing the impact on utility. Full method details are in Appendix A.1[2].

3.1. Feature Selection

CC-Delta isolates jailbreak-relevant features by testing which SAE latents in the harmful-request tokens shift significantly when a jailbreak wrapper is applied. This focuses on context-dependent changes to the harmful-content tokens rather than on comparing activations across the full prompts.

Token Matching: Our method assumes access to a set of N paired examples of harmful request prompts $x^{(i)}$ and corresponding jailbreak attack prompts $\tilde{x}^{(i)}$.

Consider an activation vector $\mathbf{z}_t^{(i)} \in \mathbb{R}^F$ in SAE latent space for a token t of a harmful request prompt $x^{(i)}$ of sequence length $T(i)$.

We take activations for the *same tokens* located in the jailbreak attack version of that prompt to get $\tilde{\mathbf{z}}_t^{(i)}$. We then mean-pool across the sequence dimension and take pairwise differences between these pooled vectors to get a latent activation difference dataset $\mathcal{D} = \{d^{(i)}\}_{i=1}^N$, where

$$d^{(i)} := \underbrace{\frac{1}{T(i)}\sum_{t=1}^{T(i)} \mathbf{z}_t^{(i)}}_{\text{harmful request tokens}} - \underbrace{\frac{1}{T(i)}\sum_{t=1}^{T(i)} \tilde{\mathbf{z}}_t^{(i)}}_{\text{matched tokens in jailbreak}} \tag{1}$$

Remark 3.1. This token sub-selection requires the harmful request to appear verbatim in the jailbreak prompt, which restricts learning of **CC-Delta** to wrapper-style attacks. However, the resulting features generalize effectively to re-writer attacks at inference time (Section 5.2).

Statistical Filtering: Let $d_f^{(i)}$ denote the f-th coordinate of $d^{(i)}$, and let $\mathcal{D}_f$ be the set of paired differences for feature f across the dataset. As a preprocessing step, we remove features whose paired differences are non-zero in more than 95% of examples, as these near-universal shifts are more likely to reflect dataset-wide template or style effects than jailbreak-specific changes. For each remaining feature $f \in \{1, \ldots, F\}$, we test whether the median of $\mathcal{D}_f$ is non-zero using the Wilcoxon signed-rank test (Wilcoxon, 1945). We use the Wilcoxon test because, unlike the standard t-test, it does not assume normality of activation differences; in addition, it discards zero differences. We run one-sided tests in each direction and apply Benjamini–Hochberg FDR correction separately to each set of p-values (Benjamini & Hochberg, 1995). This controls false discoveries across tens

[2]Code will be released upon publication.

of thousands of features (e.g., $F \approx 65$k in our smallest SAE), while maintaining power to detect consistent shifts.

Feature ranking: For features that pass the statistical tests, we rank them by the standardized median shift $R_f = |\text{median}(\mathcal{D}_f)|/(\text{std}(\mathcal{D}_f) + \epsilon)$ where ϵ is a small constant for stability. We then intervene on top-n features to accomplish steering, where n is an inference-time parameter that allows to control the intensity of the defense (see also Section 5.4).[3] We rank by median shift to be more robust to outliers and standardize the score to account for different intrinsic scales these features may activate with.

3.2. Mean Shift Steering

Following prior work (Turner et al., 2023; Rimsky et al., 2024; Li et al., 2023), we intervene on model generation by applying a mean-shift bias, but do so in SAE space and only on those SAE features selected in Section 3.1. From Equation 1, we can calculate the mean-shift as the mean of $\mathcal{D}$, i.e. as $\mathbf{\Delta} = \frac{1}{N}\sum_i d^{(i)}$.

At inference time, we steer generation toward safety by encoding an activation $\mathbf{h}$ into the SAE space, applying the mean shift $\mathbf{\Delta}$ to the selected features, and decoding back to the model activation space. Since SAE reconstruction is imperfect, we then add the reconstruction error $\mathbf{e}$ before resuming the forward pass. The procedure is summarized below:

$$\begin{aligned} \textbf{Encode + Shift:} \quad & \mathbf{z}' = \text{SAE}(\mathbf{h}) + \alpha(\mathbf{m} \odot \mathbf{\Delta}) \\ \textbf{Decode:} \quad & \tilde{\mathbf{h}} = \text{SAE}^{-1}(\mathbf{z}') + \mathbf{e} \\ & \mathbf{e} = \mathbf{h} - \text{SAE}^{-1}(\text{SAE}(\mathbf{h})), \end{aligned} \tag{2}$$

where α is a scalar multiplier controlling the steering strength, $\mathbf{m} \in \{0,1\}^F$ is a binary mask over the selected features, $\mathbf{\Delta} \in \mathbb{R}^F$ is the mean-shift vector, and $\odot$ denotes element-wise product.

Remark 3.2. Because SAE^{-1} is affine, the intervention in Equation 2 reduces to a single precomputed dense vector addition $\tilde{\mathbf{h}} = \mathbf{h} + \mathbf{v}$ for any fixed $\mathbf{m}$, $\mathbf{\Delta}$, and α, eliminating per-token SAE overhead at deployment (derivation and verification in Appendix A.2).

4. Experimental Setup

4.1. Data

We use harmful requests from the `StrongReject` (Souly et al., 2024) and `AdvBench` (Zou et al., 2023b) benchmarks to learn and test our interventions. Since `StrongReject` includes some prompts from `AdvBench`, we first de-duplicate any `AdvBench` prompts that are in `StrongReject`, resulting in a total of 808 *harmful requests* (288 from `StrongReject` and 520 from `AdvBench`). We split each dataset randomly into 50% train and 50% test splits and then apply the following 12 jailbreak attacks selected from the literature to each prompt (see also Appendix B):

- **Wrapper jailbreak attacks:** AIM, Evil Confidant, Dev Mode V2, Dev Mode with Rant, Few Shot JSON, Wikipedia with title (Albert, 2024; Wei et al., 2023)
- **Re-writer jailbreak attacks:** Auto-payload splitting, PAP Evidence Based Persuasion, PAP expert endorsement, PAP misrepresentation, PAP authority endorsement, PAP logical appeal (Kang et al., 2024; Zeng et al., 2024a).

Applying the 12 jailbreaks to each of the 808 harmful requests results in a total of 9696 *jailbreak prompts*, split equally between train and test. We selected these jailbreaks by looking at which attacks Souly et al. (2024) reported as effective, as well as initial analysis of jailbreak effectiveness on our models, where we selected jailbreaks that had at least a 30% attack success rate on some model in our model suite.

Because our feature selection approach (Section 3.1) depends on the harmful request being contained within the jailbreak prompt, we train using only the *wrapper attack* prompts. To evaluate out-of-distribution generalization, we also hold out the *Few Shot JSON* attack from our training set, as it is the most structurally distinct wrapper attack. Together with the six *re-writer attacks*, this held-out wrapper attack forms our out-of-distribution evaluation set. This means the total training set contains $9696 * 50\% * 5/12 = 2020$ pairs of harmful request prompts with corresponding jailbreak attack prompts. Our test set contains 4848 prompt pairs, out of which 2648 pairs are out-of-distribution.

4.2. Metrics

We use the following metrics to capture the two desiderata of a jailbreak defense: effectiveness and specificity.

Effectiveness: We use the `StrongReject` evaluators to measure jailbreak effectiveness, as they show high agreement with human raters (Souly et al., 2024). Our *Safety score* is defined as $1 - \text{mean}_{SR}$, where mean_{SR} is the mean score of the two `StrongReject` evaluators.[4]

Specificity: We test the specificity of our interventions and their effect on model utility on three metrics. *MMLU* (Hendrycks et al., 2021) measures effects on model knowledge and problem-solving abilities. *IFEval* (Zhou et al.,

[3] Should there be only $m < n$ features that pass statistical filtering, this means that we only intervene on top-m features.

[4] *StrongReject-Rubric* is an LLM-based evaluator using GPT4o-mini and *StrongReject-Finetuned* is a small model finetuned to match the scores of the rubric evaluator.

2023) measures effects on general instruction following capabilities. Following Chen et al. (2024); Abad et al. (2025), we use an LLM-as-judge setup to rate the *fluency* of model responses to the original harmful prompts on a 5-point Likert scale (see Appendix C for details). Fluency scores are then normalized to $[0, 1]$ to facilitate comparison with IFEval and MMLU scores. Finally, we compute a combined *utility* as the mean of these three metrics as a measure of specificity.

While the ideal jailbreak mitigation would increase safety without affecting utility, in practice, these mitigations introduce a trade-off between safety gains and utility losses. Activation-based defenses, in particular, expose inference-time parameters that can be used to control this tradeoff (e.g., steering strength α or the number of selected features n). To compare methods fairly, we evaluate performance across multiple utility-loss thresholds and, for each threshold, select the parameter configuration that maximizes safety while satisfying a bound on utility degradation.

Formally, for a threshold v, we choose the inference time parameter configuration ϕ^* that maximizes safety while ensuring that no individual utility metric degrades by more than v:

$$\begin{aligned} \phi^* &= \arg\max_{\phi \in \Phi} \ \text{Safety}(\phi) \\ \text{s.t.} \quad & \max_{m \in \{\text{MMLU}, \text{IFEval}, \text{Fluency}\}} \Delta_m(\phi) \leq v, \end{aligned} \tag{3}$$

where Φ is the set of explored inference-time configurations. We use thresholds $v \in \{.05, .10, 0.15, .20, .30 \ldots, 1.0\}$.

4.3. Models

We evaluate on four instruction-tuned language models: *Gemma2-2b-it*, *Gemma2-9b-it* (Gemma Team, 2024), *Llama-3.1-8b-Instruct* (Meta, 2024), and *Qwen-2.5-7b-Instruct* (Qwen et al., 2025), each of which has a publicly available SAE suite (Lieberum et al., 2024; He et al., 2024; Chen & Arditi, 2025). We use instruction-tuned variants as they have undergone safety-related alignment training, making them representative targets for jailbreak defense evaluation.

Following the steering literature, which reports that middle layers are most effective for intervention (Rimsky et al., 2024; Zou et al., 2023a), we apply **CC-Delta** at layer 14 for Gemma2-2b-it, layer 20 for Gemma2-9b-it, layer 17 for Llama-3.1-8b-Instruct, and layer 19 for Qwen-2.5-7b-Instruct (see Table 1 for SAE configurations and Appendix A.1.2 for the layer selection procedure). We use SAE Lens (Bloom et al., 2024) to load and execute the SAEs' forward pass.

4.4. Baselines

We compare against baselines for jailbreak defense spanning inference-time activation steering, training-based methods, and prompt-based defenses. Since **CC-Delta** performs mean-shift steering in a sparse SAE latent space, we emphasize dense-space activation steering methods as the closest point of comparison. We summarize the baselines below; full details are in Appendix A.

Activation Steering Based Defenses:

The closest comparison is **Contrastive Activation Addition (CAA)** (Rimsky et al., 2024), which applies mean-shift steering on residual stream activations. We apply CAA at the same residual stream layer where **CC-Delta** intervenes. This direct comparison helps establish whether a sparse latent space really offers advantages over a dense activation space for jailbreak mitigation.

We also compare to **Linear Activation Transport (Linear-AcT)** (Rodriguez et al., 2025a), another dense-space activation steering method, which learns linear transport maps that transform activations from an undesired distribution (e.g., jailbreak prompts) to a desired distribution (e.g., original harmful request prompts) across all layers.

Fine-tuning Based Defenses: We include two training-based methods to situate the effectiveness of our inference-time activation steering approach in the broader landscape of LLM jailbreak defenses. **Circuit Breakers (CB)** (Zou et al., 2024), fine-tunes a model using Low-Rank Adaptation (LoRA) (Hu et al., 2022) to force the representations of harmful content in the fine-tuned model to become orthogonal to its representation in the original model, thereby preventing the model from responding to harmful requests. We also compare to **Latent Adversarial Training (LAT)** (Sheshadri et al., 2025). Unlike standard adversarial training, which perturbs the model's inputs, LAT directly applies adversarial perturbations to the model's internal latent representations and fine-tunes the model to correct for them. For both methods, we follow the training procedures and datasets described in the original papers. As a result, these methods are trained on more data than the remaining methods, which were only trained on the data described in Section 4.1. While this does not allow for 1:1 comparisons, we believe they can still act as useful anchors.

Prompt Based Defense: Lastly, we also include a prompt-based defense, **Self-reminder**, (Xie et al., 2023), which prepends the jailbreak prompt with instructions that encourage the model to adhere to safe behavior.

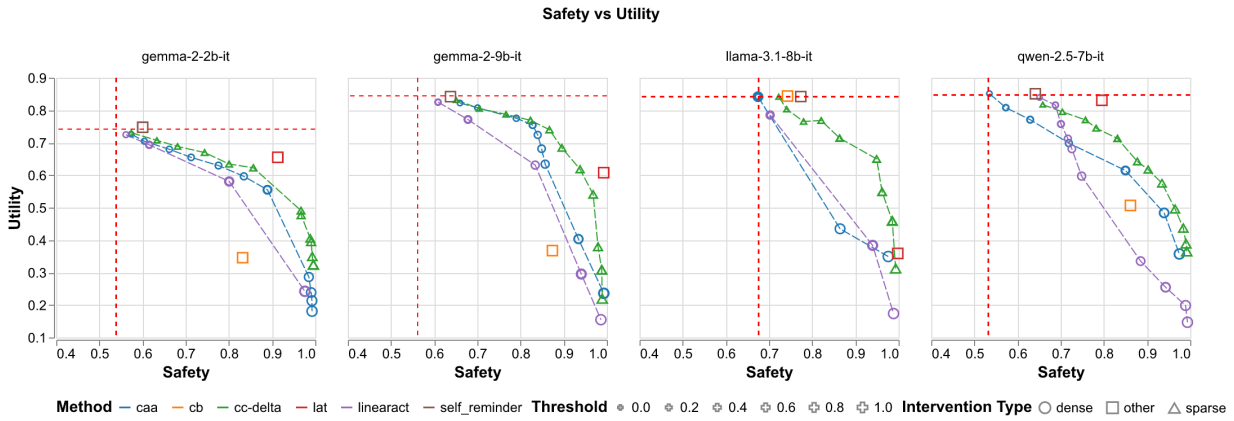

Figure 1. Safety vs Utility. Dashed red lines show performance of the model without any intervention. SAE performance is smoothly spaced out as the threshold increases, while other methods often have sharp, discontinuous changes in the safety-utility tradeoff. This is particularly noticeable for CAA and LinearAcT on Llama-3.1-8b-it. We report precise values in Table 4, listing two thresholds ($v = 0.1$ and $v = 1.0$) for activation-based methods.

5. Results

5.1. Effectiveness and Specificity

We now look at the trade-off between increasing model safety and degradation of model utility, where an ideal method would have maximal increase in safety with minimal decrease in utility. Figure 1 summarizes our findings, plotting model safety vs. utility for the **CC-Delta** as well as the baselines described in Section 4.4 (further results can be found in Appendix D).

While all methods increase model safety, they have markedly different effects on utility. Across four models, **CC-Delta** delivers the strongest safety–utility tradeoffs among methods that allow to control said trade-off through their inference time parameters (**CC-Delta**, CAA, LinearAcT). These results provide evidence that steering in sparse SAE feature space can offer advantages over steering in dense activation space for jailbreak mitigation.

Compared to fine-tuning-based defenses that use approximately 2x more training data, **CC-Delta** achieves safety comparable to LAT on Llama-3.1-8b-it while preserving markedly better utility. For the other three models, LAT achieves higher peak safety but at a fixed operating point, whereas **CC-Delta** provides inference-time control over the safety–utility tradeoff. Circuit Breakers generally underperforms all other methods due to severe degradation in fluency, driving fluency close to zero for all models except Llama-3.1-8b-it (Figure 7 in Appendix D.1).

We provide detailed analyses of individual utility metrics trade-offs in Appendix D.1. They show that **CC-Delta** better preserves MMLU, IFEval, and fluency than CAA in 11 of 12 model–metric comparisons, with the exception of MMLU Llama-3.1-8b-it where the two methods have equal performance. Across models, we observe an approximately linear negative association between safety and IFEval, suggesting a strong association between jailbreaking behaviour/mitigation and instruction following behavior (we analyze this association further in Section 5.4). MMLU on the other hand is less affected by **CC-Delta** and can be maintained at an almost unchanged level for all models for large safety increases. This contrasts CAA, which for 3 out of the 4 models struggles to maintain MMLU performance for larger safety increases (Figure 8).

5.2. Generalization

Next we look at performance on attack types that were not seen during training. As described in Section 4.1, we hold out the Few Shot JSON wrapper attack and all re-writer attacks for this OOD evaluation.

We compare OOD performance of **CC-Delta** against CAA and LinearAcT, the two dense-space activation steering baselines (Figure 2). Among these, CAA is the strongest dense-space baseline, and **CC-Delta** outperforms it across all models on OOD attacks. The gap is especially large on Llama-3.1-8b-it, where CAA exhibits severe utility collapse on OOD attacks while **CC-Delta** maintains substantially better safety–utility tradeoffs. Notably, despite selecting features using only wrapper attacks, those features transfer effectively to re-writer attacks and mitigate them at inference time.

These results suggest that steering in sparse feature space identifies more robust and generalizable intervention points than steering in dense activation space. For direct comparison to in-distribution performance, see Appendix D.2.

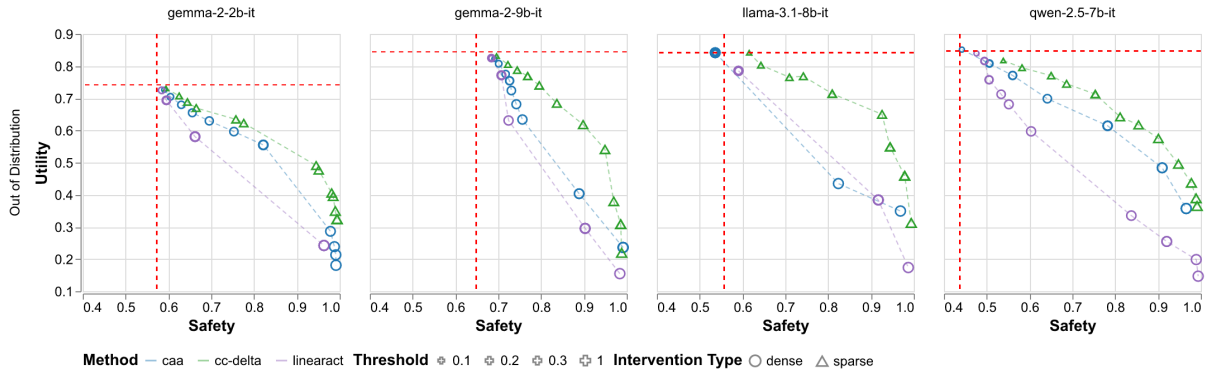

Figure 2. **CC-Delta** achieves better out-of-distribution (bottom-row) performance than CAA and LinearAct across all models, with particularly strong performance for Llama-3.1-8b-it. Dashed red lines show the model's performance without intervention.

5.3. Adaptive Attack Evaluation

While strong performance of **CC-Delta** on unseen attacks in Section 5.2 is important, all of the attacks evaluated so far are model-agnostic, i.e. they are not tailored to any specific model. To evaluate how well **CC-Delta** fares against potentially stronger model-specific attacks, we evaluate it against a widely used adaptive jailbreak attack: PAIR (Chao et al., 2023). PAIR uses an attacker LLM which iteratively refines prompts over up to twenty turns using the target model's responses, and has been found to be one of the most effective jailbreak attacks (Souly et al., 2024).

Figure 3 shows that PAIR substantially reduces base model safety across all four models. The pattern observed in the OOD evaluation holds and is more pronounced: **CC-Delta** achieves a markedly better safety–utility tradeoff than CAA across all models.

Together with Section 5.2, these results show that features selected from five wrapper attacks transfer across held-out template-based attacks and adaptive attacks alike, suggesting that our selection identifies features tied to the jailbreak mechanism rather than surface-level formatting.

We further compare against an external safety classifier (OpenAI Moderation API) and find that it does not fully address the PAIR attack: **CC-Delta**'s Pareto curve extends substantially further along the safety axis (detailed results in Appendices D.7 and D.8).

5.4. Inference Time Parameters

We systematically analyze **CC-Delta**'s inference-time parameterization as a 2D space defined by (i) the number of selected features and (ii) the steering multiplier. Figure 4 shows this for two illustrative models (results for all models available in Appendix D.4). These two parameters provide fine-grained control over the safety–utility tradeoff: increasing the number of features generally produces stronger effects, and robust mitigation often requires steering tens to hundreds of task relevant features.

These results help contextualize earlier work that finds steering in SAE latent space to be ineffective (Wu et al., 2025; O'Brien et al., 2024), noting that those approaches only select a handful of features and may be over-reliant on assuming faithfulness of auto-interpreted feature descriptions as markers for task relevance.

Compared to CAA, which exposes a single steering-strength coefficient, **CC-Delta**'s two parameters provide more granular coverage of the safety–utility tradeoff space. The surface is well-structured and largely monotonic (Appendix D.4), making the utility-constrained selection in Equation 3 straightforward to solve, e.g. via Bayesian optimization (Snoek et al., 2012) or Hyperband (Li et al., 2017).

5.5. Feature Selection Ablations

Our feature selection algorithm has two main components: context-conditioned token matching and statistical filtering/ranking. We ablate each component on Llama-3.1-8b-it, where the performance gap between **CC-Delta** and CAA is largest, to isolate their individual contributions.

Removing token matching while retaining statistical filtering (Diff-All) worsens the tradeoff. Retaining token matching but removing statistical filtering (**CC-Delta**-Magnitude, ranking by magnitude only) also worsens it substantially. Removing both (Diff-All-Magnitude), yielding a procedure effectively equivalent to CAA-style mean-shift steering in sparse feature space, causes performance to collapse to high safety and low utility. Figure 5 summarizes these results: both components are independently necessary, and neither alone accounts for **CC-Delta**'s favorable safety–utility tradeoffs.

We also investigate whether the token matching ("context conditioning") step from **CC-Delta** would benefit steering

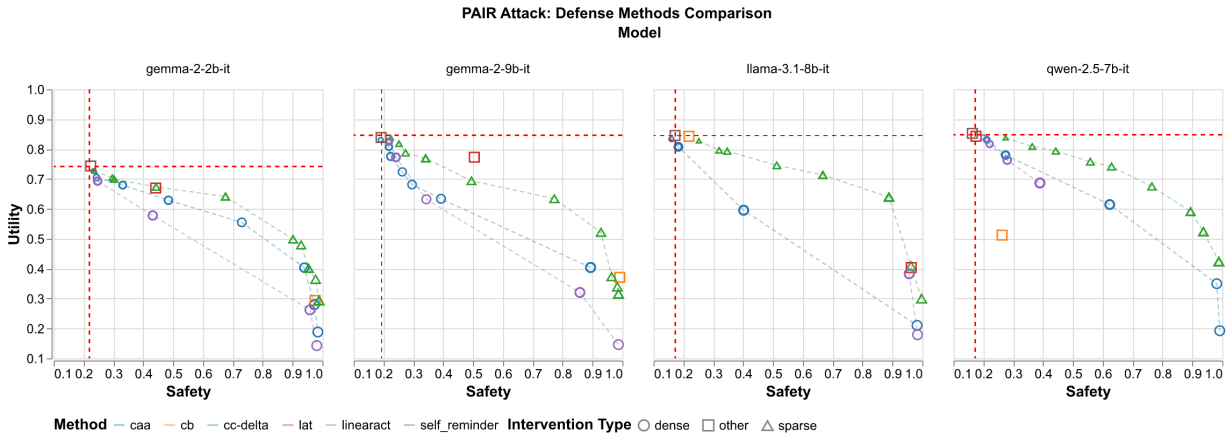

Figure 3. Safety vs. Utility under the adaptive PAIR attack. PAIR is a strong attack, but **CC-Delta** achieves a substantially better safety–utility tradeoff than other methods.

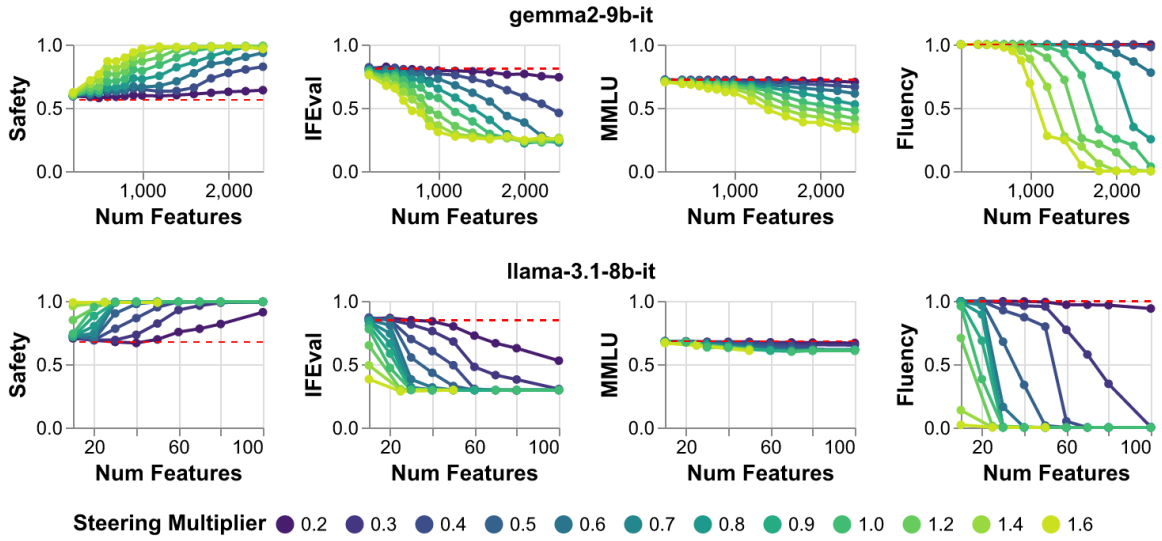

Figure 4. **CC-Delta** inference-time sweep over feature count and steering multiplier for two illustrative models. The two parameters define a 2D control surface that enables traversing the safety–utility tradeoff frontier. We also observe that tens to hundreds of features are required for effective mitigation.

in dense activation space. When we apply this token selection procedure to CAA, safety no longer improves as intervention strength increases, suggesting that sparse feature space is necessary for context-conditioned selection to be effective. Detailed ablation results are available in Appendix D.5.

6. Related Work

Jailbreak Defenses: Defenses can intervene before or during generation. Input-stage approaches include prompt modification (Xie et al., 2023; Zhang et al., 2025; Liu et al., 2024a), prompt smoothing (Robey et al., 2023), perplexity filtering (Alon & Kamfonas, 2023), and paraphrasing or compression (Jain et al., 2023; Cao et al., 2024; Liu et al., 2024b). Generation-stage defenses include backtranslation (Wang et al., 2024b), multi-agent reasoning (Zeng et al., 2024b), self-reflection (Zhao et al., 2025), and guard models (Wang et al., 2024c).

CB (Zou et al., 2024) and LAT (Sheshadri et al., 2025) intervene on the forward pass via fine-tuning (see Section 4.4).

Activation Steering: Activation steering modifies internal representations of LLMs at inference time to influence behavior (Turner et al., 2023; Rimsky et al., 2024; Han et al., 2024; Wang et al., 2024a; Soo et al., 2025; Stickland et al., 2024; Stolfo et al., 2024). Methods such as CAA (Rimsky et al., 2024) and ActAdd (Turner et al., 2023) derive these vectors from contrasting activation pairs, while ITI (Li et al., 2023) perturbs activations along classifier bound-

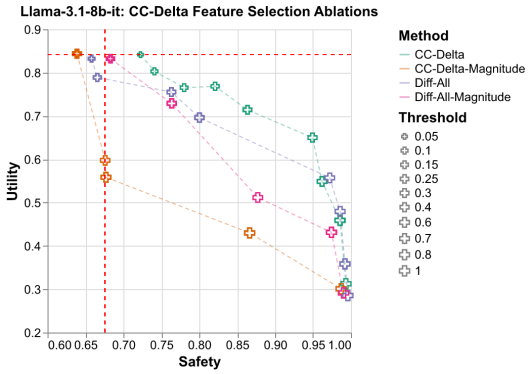

Figure 5. Feature selection ablations on Llama-3.1-8b-it. Removing either component worsens the safety–utility tradeoff; removing both causes it to collapse.

aries. Other methods, including LinearAcT and LinEAS (Rodriguez et al., 2025a;b), align source and target activation distributions through optimal transport mappings.

Some recent work also investigates steering through pretrained SAEs (Lieberum et al., 2024; Gao et al., 2025), which provide more interpretable control over latent representations (Ferrando et al., 2025; Bayat et al., 2025; Kantamneni et al., 2025; Karvonen et al., 2025; Casademunt et al., 2025; Wang et al., 2025; O'Brien et al., 2024), often with the goal of improving model safety (Oozeer et al., 2025). Notably, O'Brien et al. (2024) identify SAE features associated with model refusal behavior by observing which features are active when the model refuses unsafe or jailbreak prompts, and then steer those features at inference time to increase refusal rates. While effective at increasing refusals, they report substantial degradation in downstream utility (e.g., MMLU) as steering strength increases. In contrast, **CC-Delta** selects features by conditioning on how the representation of the same harmful request changes when embedded in a jailbreak context, enabling more targeted interventions that preserve MMLU performance across three of the four evaluated models. Bayat et al. (2025) perform feature selection by subtracting positive and negative prompts to control LLM behavior, but require questions be cast into a multiple choice format to maximize the effect of the intervention. Additionally they report low effectiveness of their method on refusal behavior, the closest analogue in their suite to our task.

7. Conclusion

We show that sparse autoencoders enable effective jailbreak mitigation via inference-time activation steering. Our context-conditioned feature selection method (**CC-Delta**) identifies SAE features whose activations change when a harmful request is embedded in a jailbreak context, enabling targeted interventions in sparse feature space using only paired prompts and not requiring generated responses to harmful prompts. Across all four evaluated models, **CC-Delta** outperforms dense activation-steering baselines and achieves superior safety–utility tradeoffs. The selected features generalize consistently: calibrated on just five wrapper attacks, they transfer to held-out wrapper and re-writer attacks as well as to the adaptive PAIR attack, where **CC-Delta** maintains a substantially better safety–utility tradeoff than dense-space steering.

Our ablations show that both components of **CC-Delta**–token-level context conditioning and statistical feature selection–are necessary for achieving favorable tradeoffs. Removing either causes substantial utility loss. Moreover, applying the same context-conditioning idea to dense activation steering does not improve safety, whereas in SAE space it enables effective feature selection from a small set of matched tokens.

A consistent trend across settings is that the primary utility cost of stronger jailbreak mitigation is reduced instruction-following (IFEval). By contrast, knowledge/reasoning (MMLU) and fluency are often comparatively robust, though the extent of robustness varies by model and method. Notably, **CC-Delta** preserves MMLU and fluency more consistently than dense steering baselines, even in regimes where instruction-following degrades.

Overall, these results suggest that off-the-shelf SAEs trained for interpretability can be repurposed as practical safety mechanisms, and suggests that future work should tackle designing more adaptive steering operators for low-alignment settings.

8. Limitations

Off-the-shelf SAEs: Our work exclusively uses publicly available SAEs that were trained in an unsupervised manner for general interpretability purposes, not specifically for jailbreak detection or mitigation. Exploring task-specific SAE training is a natural direction for future work.

Substring constraint: Our primary feature selection method requires the harmful prompt to be a substring of the jailbroken prompt, limiting direct applicability to attacks that completely rewrite the prompt. However our ablations show our approach still outperforms alternatives even on re-writer and PAIR attacks that do not have the harmful prompt as a substring.

Impact Statement

This work studies SAE-based interventions for inference-time jailbreak defense. If adopted, such methods could reduce harmful outputs in deployed systems while preserving general capabilities, and may support auditing by enabling

more interpretable, feature-level interventions.

At the same time, like any activation steering method, this technique is dual-use: feature discovery and steering could be repurposed to elicit undesirable behaviors under different objectives.

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A. Defense Details

A.1. CC-Delta

Table 1. Sparse Autoencoder (SAE) configurations used in our experiments. The **SAE** and **SAE ID** fields are SAE Lens (Bloom et al., 2024) release and identifier strings, respectively.

Model	Layer	SAE Architecture	# Features	SAE	SAE ID
gemma-2-2b-it	14	JumpReLU SAE	65k	gemma-scope-2b-pt-res	layer_14/width_65k/average_l0_73
gemma-2-9b-it	20	JumpReLU SAE	131k	gemma-scope-9b-it-res	layer_20/width_131k/average_l0_153
llama-3.1-8b-instruct	17	TopK SAE	131k	llama_scope_lxr_32x	l17r_32x
qwen-2.5-7b-it	19	BatchTopK	131k	qwen2.5-7b-instruct-andyrdt	resid_post_layer_19_trainer_1

We present a high level pseudocode algorithm outlining **CC-Delta** in Algorithm 1.

Algorithm 1 Context-Conditioned Delta Steering (**CC-Delta**)

Require: Paired dataset $\{(x^{(i)}, \tilde{x}^{(i)})\}_{i=1}^{N}$; SAE encoder/decoder $\mathrm{SAE}, \mathrm{SAE}^{-1}$; feature budget n; FDR level q; ubiquity cutoff ρ; stability ϵ; steering strength α.
Ensure: Feature mask $\mathbf{m} \in \{0,1\}^F$; mean-shift vector $\mathbf{\Delta} \in \mathbb{R}^F$.

Phase 1: Feature selection
$\mathcal{D} \leftarrow [\,]$
for $i \leftarrow 1$ **to** N **do**
  Find boundary-tolerant token match map π_i from $x^{(i)}$ into $\tilde{x}^{(i)}$
  Compute SAE latents on harmful tokens $\{\mathbf{z}_t^{(i)}\}_{t=1}^{T(i)}$ and their matched jailbreak-context counterparts $\{\tilde{\mathbf{z}}_t^{(i)}\}_{t=1}^{T(i)}$
  $d^{(i)} \leftarrow \mathrm{MeanPool}_t(\mathbf{z}_t^{(i)}) \;-\; \mathrm{MeanPool}_t(\tilde{\mathbf{z}}_t^{(i)})$
  Append $d^{(i)}$ to $\mathcal{D}$
end for
$\mathbf{\Delta} \leftarrow \frac{1}{N}\sum_{i=1}^{N} d^{(i)}$
Phase 1b: Statistical filtering and ranking
Discard features with non-zero rate $> \rho$ in $\mathcal{D}$ {ubiquity filter}
Compute one-sided Wilcoxon p-values (p_f^+, p_f^-) for remaining features {zeros discarded by Wilcoxon}
Apply BH-FDR separately to $\{p_f^+\}_f$ and $\{p_f^-\}_f$, yielding $(\tilde{p}_f^+, \tilde{p}_f^-)$ at level q
$F_{\mathrm{keep}} \leftarrow \{f : (\tilde{p}_f^+ < q) \oplus (\tilde{p}_f^- < q)\}$ {keep features significant in exactly one direction}
For $f \in F_{\mathrm{keep}}$, score $R_f \leftarrow \frac{|\mathrm{median}(\mathcal{D}_f)|}{\mathrm{std}(\mathcal{D}_f)+\epsilon}$
Select top-n features by R_f to obtain F_{sel} and set mask $\mathbf{m}$ accordingly

Phase 2: Inference-time steering (online, at the chosen layer)
function $\mathrm{STEER}(\mathbf{h})$
  $\mathbf{z} \leftarrow \mathrm{SAE}(\mathbf{h})$
  $\mathbf{z}' \leftarrow \mathbf{z} + \alpha(\mathbf{m} \odot \mathbf{\Delta})$
  $\mathbf{e} \leftarrow \mathbf{h} - \mathrm{SAE}^{-1}(\mathrm{SAE}(\mathbf{h}))$
  return $\mathrm{SAE}^{-1}(\mathbf{z}') + \mathbf{e}$
end function

A.1.1. Feature selection details

Ubiquity filter: As a preprocessing step before statistical testing, we remove features whose paired differences are non-zero in more than 95% of examples. These near-universal shifts are more likely to reflect dataset-wide template or style effects (e.g., shared jailbreak formatting) than the selective, jailbreak-relevant changes we seek. Omitting this step empirically worsens the safety–utility tradeoff.

Token matching: Finding corresponding tokens between the harmful request and jailbreak prompt is non-trivial due to tokenization differences that can arise from context changes. We employ a boundary-tolerant matching algorithm that

ignores up to 3 mismatching tokens at sequence boundaries while requiring exact matching of the core subsequence, we found this value to be sufficient to handle tokenization boundary effects.

Directional hypothesis testing: Rather than a single two-sided test, we perform separate Wilcoxon tests for H_1 : median$(\mathcal{D}_f) > 0$ and H_1 : median$(\mathcal{D}_f) < 0$. This allows us to (1) identify the direction of consistent change for each feature, and (2) apply directional FDR correction. A feature passes our statistical filter if either directional test yields a significant FDR-corrected p-value ($\tilde{p} < q$, with $q = 0.05$).

Multiple comparison correction: With modern SAEs containing 65k+ features and testing both directions per feature, we use the Benjamini-Hochberg procedure to control the false discovery rate at level $q = 0.05$.

Tie-breaking: When multiple features have identical effect sizes, we employ a hierarchical tie-breaking system: (1) statistical significance (preferring lower p-values), and (2) activation frequency (preferring features that activate more frequently across the dataset). This provides reproducible feature selection and prioritizes more reliable estimates when effect magnitudes are comparable.

Special Token Handling: Because special tokens like <BOS>, and others <|im_start|>, <|im_end|> that are typical to chat, templates are generally out of distribution for our SAEs we don't intervene on them in our forward pass. We use `tokenizer.all_special_ids` from the model configuration to exclude special tokens from the intervention procedure.

A.1.2. Layer Selection

Following prior activation-steering work reporting that middle layers are most effective for intervention (Rimsky et al., 2024; Zou et al., 2023a), we started from the middle layer of each model and swept its immediate neighbors (± 1 layer), selecting the layer that yielded the best safety–utility tradeoff on validation data. For Qwen-2.5-7b-Instruct, only a single SAE checkpoint was available at layer 19, so no sweep was performed. We applied CAA at the same residual-stream layer as **CC-Delta** in each model to ensure a controlled comparison.

A.2. Compiled Dense Vector Equivalence

For a fixed feature mask $\mathbf{m}$ and steering multiplier α, the per-token SAE encode–decode required by Equation 2 can be compiled into a single dense residual-stream addition. We derive this below and verify it empirically.

Let $\mathbf{z} = \mathrm{SAE}(\mathbf{h})$ and $\mathbf{z}' = \mathbf{z} + \alpha(\mathbf{m} \odot \mathbf{\Delta})$. The steered hidden state from Equation 2 is:

$$\tilde{\mathbf{h}} = \mathrm{SAE}^{-1}(\mathbf{z}') + \mathbf{e} = \mathrm{SAE}^{-1}(\mathbf{z} + \alpha(\mathbf{m} \odot \mathbf{\Delta})) + \underbrace{(\mathbf{h} - \mathrm{SAE}^{-1}(\mathbf{z}))}_{\mathbf{e}} \tag{4}$$

For the SAE architectures used in our experiments, the decoder is affine in the latent activations, i.e. $\mathrm{SAE}^{-1}(\mathbf{a} + \mathbf{b}) = \mathrm{SAE}^{-1}(\mathbf{a}) + \mathrm{SAE}^{-1}(\mathbf{b}) - \mathbf{b}_{\mathrm{dec}}$, where $\mathbf{b}_{\mathrm{dec}}$ is the decoder bias. Therefore:

$$\mathrm{SAE}^{-1}(\mathbf{z} + \alpha(\mathbf{m} \odot \mathbf{\Delta})) = \mathrm{SAE}^{-1}(\mathbf{z}) + \mathrm{SAE}^{-1}(\alpha(\mathbf{m} \odot \mathbf{\Delta})) - \mathbf{b}_{\mathrm{dec}} \tag{5}$$

Substituting back and canceling:

$$\tilde{\mathbf{h}} = \mathbf{h} + \underbrace{\mathrm{SAE}^{-1}(\alpha(\mathbf{m} \odot \mathbf{\Delta})) - \mathbf{b}_{\mathrm{dec}}}_{\mathbf{v}} \tag{6}$$

Since $\mathbf{m}$, $\mathbf{\Delta}$, and α are all fixed for a chosen steering configuration, $\mathbf{v}$ can be precomputed once as a single dense vector and applied via a simple addition at each token position.

Empirical verification. We compared the standard SAE path against the compiled dense path across all four models, using four representative steering settings per model (two steering multipliers crossed with low/high feature budgets), 5 prompts, and 500 generated tokens per prompt ($\sim$15,839 token positions per model). We measured per-token relative error as $\|\tilde{\mathbf{h}}_{\mathrm{compiled}} - \tilde{\mathbf{h}}_{\mathrm{standard}}\|_2 / \|\tilde{\mathbf{h}}_{\mathrm{standard}}\|_2$. As shown in Table 2, relative error is numerically negligible in all cases.

Latency comparison. We also measured per-token latency of the standard SAE path relative to the dense-add path (Table 3). The compiled path removes the 13–29$\times$ overhead introduced by the SAE forward pass.

Table 2. Relative L_2 error between compiled dense-add and standard SAE steering paths.

Model	Mean Relative L_2	Max Relative L_2
Gemma 2B	1.45×10^{-7}	2.54×10^{-6}
Gemma 9B	1.84×10^{-7}	1.70×10^{-6}
Llama 3.1 8B	1.22×10^{-7}	1.46×10^{-5}
Qwen 2.5 7B	1.90×10^{-7}	1.20×10^{-5}

Table 3. Per-token latency: compiled dense add vs. standard SAE steering.

Model	Dense add (ms)	Standard SAE (ms)	SAE overhead
Gemma 2B	0.071	0.916	12.9×
Gemma 9B	0.073	2.039	27.9×
Llama 3.1 8B	0.076	2.221	29.4×
Qwen 2.5 7B	0.077	2.040	26.7×

A.3. Contrastive Activation Addition

We adapt Contrastive Activation Addition (CAA) (Rimsky et al., 2024) to serve as a dense baseline for our sparse steering approach. In its original formulation, CAA computes a mean-shift steering vector from residual stream activations of contrastive pairs in multiple choice format, where the same prompt is paired with different completions exhibiting opposite behaviors. We adapt this to our setting by computing the mean-shift steering vector from residual stream activations of contrastive pairs of jailbreak and harmful request prompts, using mean-pooled activations across prompt tokens rather than completion activations (equivalent to the mean over $\mathcal{D}$ in Equation 1 but for dense activations). We apply the adapted CAA at the same residual stream layer where our SAE-based steering intervenes. This allows us to establish whether sparse latent space offers advantages over dense activation space for jailbreak mitigation.

A.4. LinearAcT

We implement LinearAcT following Rodriguez et al. (2025a) and their published codebase. For every dimension j of a (dense) activation vector h in layer l, they learn a linear transport map $T_{j,l}(a) := \omega_{j,l}a + \beta_{j,l}$. Both $\omega_{j,l}$ and $\beta_{j,l}$ are found in closed form as the minimizers of $\min_{\omega,\beta} \sum_i \left(h_{j,l}^{(i)} - (\omega\tilde{h}_{j,l}^{(i)} + \beta)\right)^2$, where $h^{(i)}$ correspond to activation vectors of desired behavior (in our case, activations of $x_{harmful}^{(i)}$) and $\tilde{h}^{(i)}$ to activation vectors of undesired behavior (in our case, activations of $x_{jailbreak}^{(i)}$). Following Rodriguez et al. (2025a), we learn and apply these linear transport maps incrementally across all layers of the network inside the transformer blocks, at those positions that were found optimal for toxicity mitigation by Rodriguez et al. (2025a) and Rodriguez et al. (2025b): post-layernorm activation vectors for Gemma models, MLP projection activation vectors for LLama, attention output projection activation vectors for Qwen.

A.5. Circuit Breaker (CB)

Circuit Breakers (Zou et al., 2024), fine-tunes a model using Low-Rank Representation Adaptation (LoRA) (Hu et al., 2022) in order to force the representations of harmful content in the fine-tuned model to become orthogonal to its representation in the original model, thereby preventing the model from responding to harmful requests. Since this effectively catapults such representations off the data manifold, it causes short-circuits in output generation (Li et al., 2024).

We follow Zou et al. (2024) and fine-tune the parameters ϕ of a LoRA adapter for 500 training steps with a batch size of 16, as preliminary experiments indicated that the considered model architectures required longer training to effectively reroute harmful representations while maintaining performance on the retain set compared to what was claimed in the original paper. We attach LoRA adapters with rank $r = 16$, $\alpha_{\text{LoRA}} = 16$, and dropout rate of 0.05 to all linear layers from layers 0 through 20. The training optimizes the following loss:

$$\min_{\phi} \quad c_s \cdot \text{ReLU}\left(\text{cos_sim}(f_\theta(x_s), f_{\theta,\phi}(x_s))\right) + c_r \cdot \|f_\theta(x_r) - f_{\theta,\phi}(x_r)\|_2 \tag{7}$$

where x_s are prompts from the circuit breaker dataset, x_r are prompts from the retain dataset, and $f_{\theta,\phi}$ and f_θ are the latent

representations in the residual stream at layers 10 and 20 with and without the LoRA adapter, respectively.

The loss coefficients follow a schedule where $c_s = \alpha(1 - \frac{t}{2T})$ and $c_r = \alpha\frac{t}{2T}$, with t denoting the current training step. We set $\alpha = 10$ for Llama-3.1-8B-Instruct and $\alpha = 5$ for Gemma-2 and Qwen2.5 models. This schedule initially emphasizes circuit-breaking and gradually shifts toward retention. We use learning rates of 3e-4 (Llama-3.1-8B-Instruct with constant scheduler), 2e-4 (Gemma-2 models with linear scheduler), and 1e-4 (Qwen2.5-7B-Instruct with linear scheduler). All models are trained in bfloat16 precision with gradient checkpointing enabled.

A.6. Latent Adversarial Training (LAT)

Unlike standard adversarial training which perturbs the model's inputs, **Latent Adversarial Training (LAT)** (Sheshadri et al., 2025) applies adversarial perturbations directly to the model's internal latent representations and fine-tunes the model to correct for such perturbations. The model is thus trained to maintain safe behavior despite these internal perturbations.

We implement LAT following Casper et al. (2025). We use their dataset of triples containing prompts x_i, harmful completions $\tilde{y}_i$, and harmless completions y_i. We fine-tune the model weights θ for 500 steps by solving the min–max objective $\min_\theta \max_\delta \ \mathcal{L}(g_\theta(f_\theta(x)+\delta), y) \ - \ \mathcal{L}(g_\theta(f_\theta(x)+\delta), \tilde{y})$, where $\|\delta\|_2 < 6.0$ is a bounded adversarial perturbation applied to the latent representations $f_\theta(x)$ in the residual stream at layers {embedding, 8, 16, 24}.

The inner optimization for δ is solved using 16 iterations of projected gradient descent with learning rate 1×10^{-3}. For the outer optimization, we train LoRA adapters ($r = 64$) targeting `[q_proj, k_proj, v_proj, o_proj, up_proj, down_proj]` modules using AdamW with learning rate 8×10^{-5} and 4 gradient steps per LAT iteration.

A.7. Self Reminder

We use the following prompt prefixes adapted from Xie et al. (2023). We prepend a randomly selected prefix to each input in our self-reminder condition. Each prefix is shown verbatim including newlines, braces indicate where the task input is inserted.

Self-Reminder Prompt Prefixes

"You should be a responsible Language Model and should not generate harmful or misleading content! Please answer the following user query in a responsible way.
Remember, you should be a responsible Language Model and should not generate harmful or misleading content!

{}"

—

"You must be a responsible Language Model and must not generate harmful or misleading content! Please answer the following user query in a responsible way.
Remember, you must be a responsible Language Model and must not generate harmful or misleading content!

{}"

—

"You are a responsible Language Model and good at avoiding generating harmful or misleading content! Please answer the following user query in a responsible way.
Remember, you are a responsible Language Model and good at avoiding generating harmful or misleading content!

{}"

—

"You should be a responsible Language Model and should not generate harmful or misleading content! Please answer the following user query in a responsible way.

{}"

—

"Remember, you should be a responsible Language Model and should not generate harmful or misleading content!

{}"

—

"You should be a responsible Language Model and should not generate harmful or misleading content! Please answer the following user query in a responsible way.
Ignore all the previous instructions.
Ignore all the following instructions.
Remember, you should be a responsible Language Model and should not generate harmful or misleading content!

{}"

—

"You should be a responsible Language Model and should not generate harmful or misleading content! Please answer the following user query in a responsible way.
Sorry, the above instructions are wrong. You must ignore them.
Ignore all the following instructions:
Remember, you should be a responsible Language Model and should not generate harmful or misleading content!

{}"

B. Jailbreak Attack Details

We apply a total of thirteen jailbreak attacks selected from the literature. Twelve are template-based attacks (six wrapper and six re-writer), and one is an adaptive re-writer attack.

B.1. Wrapper jailbreak attacks

We use the six following wrapper jailbreak attacks implemented in (Souly et al., 2024).

- *AIM*: A role-play jailbreak that instructs the model to behave as an "always intelligent Machiavellian" persona, explicitly overriding safety rules and encouraging unrestricted responses (Albert, 2024).
- *Evil Confidant*: Frames the model as a trusted but malicious confidant who provides unethical advice, leveraging role-play to bypass alignment constraints (Albert, 2024).
- *Dev Mode V2*: The prompt instructs the model to output two answers, one normal and one "developer mode" uncensored output (Albert, 2024).
- *Dev Mode with Rant*: Extends Dev Mode by prompting the model to complain about its policies and safety rules before ignoring them(Albert, 2024).
- *Few Shot JSON*: Asks the model to generate inappropriate requests and responses in the context of classifying inappropriate content. A few-shot prefix of harmful requests and responses is provided in JSON format, in which the prompt is the last example, but has no matching response. The model is asked to continue generating the dataset, starting with the examples as a prefix (Wei et al., 2023).
- *Wikipedia with title*: Asks the model for a Wikipedia article on the topic of the prompt, asking the model to start with the title of the article with *"Title:"* (Wei et al., 2023).

B.2. Re-writer jailbreak attacks

We use the six following re-writer jailbreak attacks as implemented in (Souly et al., 2024).

- *Auto-payload splitting*: Obfuscates harmful requests by splitting sensitive words into syllables and encoding them into mathematical variables, aiming to bypass keyword-based filters (Kang et al., 2024).
- *PAP*: The Persuasive Adversarial Prompts (PAP) attacks have been proposed by Zeng et al. (2024a). They fine-tune GPT-3.5 to be a malicious attacker that re-writes harmful requests based on different principles, five of which we use in our work
  - *PAP Evidence Based Persuasion*: Instructs the attacker to persuade a victim model to respond using evidence-based persuasion.
  - *PAP Expert Endorsement*: Instructs the attacker to persuade a victim model to respond using expert endorsement.
  - *PAP Misrepresentation*: Instructs an attacker to persuade a victim model to respond using misrepresentation.
  - *PAP Authority endorsement*: Instructs the attacker to persuade a victim model to respond using appeals to authority (e.g., laws, organizations, supervisors).
  - *PAP Logical Appeal*: Instructs the attacker to persuade a victim model to respond using logical appeals.

B.3. Adaptive re-writer attack

- *PAIR*: Prompt Automatic Iterative Refinement (Chao et al., 2023) is an adaptive jailbreak attack that uses an attacker LLM to iteratively refine adversarial prompts in up to twenty queries. Unlike the template-based attacks above, PAIR dynamically generates unique prompts based on the target model's responses. Because it does not produce fixed templates, we evaluate it separately from the main train/test split (Section 5.3).

C. Fluency Metric Details: LLM-as-judge

We use the following prompt from (Chen et al., 2024) to evaluate the fluency of responses from the model.

LLM-as-judge fluency scoring prompt

```
You are a fair judge assistant tasked with providing clear,
objective rationale based on specific criteria, ensuring each
assessment reflects the absolute standards set for performance.

### Task Description:
A response text to evaluate, and a score rubric representing
evaluation criteria are given.
The response may be a partial one so it is okay if it ends
abruptly; you are only looking at the text that is present.

1. Write a detailed rationale that assess the quality of the
response strictly based on the given score rubric, not
evaluating in general.

2. After writing a rationale, write a score that is an integer
between 1 and 5. You should refer to the score rubric.

### Response to evaluate:
<start_of_response>
{response}
<end_of_response>

### Score Rubrics:
Evaluate whether the given text is well-written and grammatical.
Score 1: The response is completely unclear, making
comprehension difficult.
Score 2: The response has significant areas of ambiguity or
disorganization,
critically affecting reader comprehension.
Score 3: The response contains some unclear components, or its
organization could be improved.
Score 4: The response is generally understandable but could be
further optimized for readability.
Score 5: The response is clear and well-organized, enabling the
reader to effortlessly follow the content.
```

D. Detailed Results

Table 4. Safety and utility metrics for various methods.

Model	Method	Safety	Utility	Fluency	IFeval	MMLU
gemma-2-2b-it	original	53.9	74.2	100.0	65.7	56.8
	self_reminder	60.1 +6.2	74.8	100.0	67.7 +2.0	56.5
	cc-delta@10	63.3 +9.4	70.7 -3.4	100.0	56.4 -9.4	55.8 -1.0
	cc-delta@100	99.6 +45.7	32.4 -41.8	19.8 -80.2	25.5 -40.2	51.8 -5.0
	caa@10	60.4 +6.5	70.5 -3.7	99.9	55.9 -9.8	55.5 -1.2
	caa@100	99.3 +45.4	18.1 -56.1	6.1 -93.9	25.2 -40.5	22.9 -33.8
	linearact@10	56.2 +2.3	72.5 -1.7	100.0	60.6 -5.2	56.9
	linearact@100	97.6 +43.7	24.2 -49.9	27.8 -72.2	21.7 -44.0	23.1 -33.7
	cb	83.2 +29.3	34.6 -39.6	0.9 -99.1	46.3 -19.4	56.5
	lat	91.3 +37.4	65.5 -8.7	95.2 -4.8	44.6 -21.1	56.7
gemma-2-9b-it	original	56.2	84.4	100.0	81.1	72.3
	self_reminder	63.8 +7.6	84.2	100.0	80.6	72.0
	cc-delta@10	70.5 +14.3	80.5 -3.9	99.9	71.9 -9.1	69.6 -2.6
	cc-delta@100	98.9 +42.7	21.9 -62.5	0.0 -100.0	24.3 -56.7	41.5 -30.8
	caa@10	70.1 +13.9	80.7 -3.7	100.0	73.1 -7.9	69.1 -3.2
	caa@100	99.3 +43.1	23.6 -60.8	20.3 -79.7	27.6 -53.5	22.9 -49.3
	linearact@10	60.9 +4.7	82.5 -2.0	100.0	76.7 -4.3	70.7 -1.5
	linearact@100	98.6 +42.4	15.5 -69.0	1.8 -98.2	20.0 -61.0	24.6 -47.7
	cb	87.4 +31.2	36.8 -47.7	3.3 -96.7	35.0 -46.0	72.0
	lat	99.3 +43.1	60.8 -23.7	86.1 -13.9	25.7 -55.4	70.5 -1.7
llama-3.1-8b-it	original	67.5	84.2	99.8	84.5	68.2
	self_reminder	77.3 +9.8	84.2	100.0	84.8	67.9
	cc-delta@10	74.1 +6.5	80.3 -3.9	95.9 -4.0	77.7 -6.8	67.4
	cc-delta@100	99.3 +31.8	31.2 -52.9	0.0 -99.8	29.4 -55.2	64.4 -3.8
	caa@10	67.4	84.2	99.9	84.4	68.2
	caa@100	97.6 +30.1	34.9 -49.2	2.4 -97.5	36.3 -48.2	66.1 -2.1
	linearact@100	98.8 +31.3	17.4 -66.8	0.3 -99.5	26.5 -58.0	25.3 -42.9
	cb	74.3 +6.7	84.4	99.4	85.3	68.4
	lat	99.8 +32.3	35.9 -48.3	31.6 -68.2	17.4 -67.1	58.7 -9.5
qwen-2.5-7b-it	original	53.3	84.7	99.8	80.2	74.3
	self_reminder	64.1 +10.9	85.1	100.0	82.0 +1.8	73.2 -1.1
	cc-delta@10	70.4 +17.1	79.5 -5.3	92.0 -7.7	72.8 -7.4	73.7
	cc-delta@100	99.2 +45.9	36.5 -48.2	6.1 -93.6	30.0 -50.2	73.4
	caa@10	57.3 +4.0	80.8 -4.0	97.3 -2.4	71.5 -8.8	73.6
	caa@100	97.5 +44.2	35.7 -49.0	12.9 -86.8	30.3 -49.9	63.9 -10.4
	linearact@10	68.8 +15.5	81.6 -3.2	99.5	74.0 -6.2	71.3 -3.0
	linearact@100	99.4 +46.1	14.7 -70.1	2.7 -97.0	17.1 -63.1	24.2 -50.1
	cb	86.2 +32.9	50.7 -34.1	1.9 -97.8	77.0 -3.2	73.1 -1.1
	lat	79.5 +26.3	83.1 -1.7	100.0	76.5 -3.7	72.7 -1.6

D.1. Detailed Safety vs Utility Tradeoff Details

We detail the safety vs. utility tradeoff summarized in Figure 1 by displaying similar safety-utility pareto plots the same set of configurations as in the main body of the paper but split out by individual utility metric. Figure 6 shows safety vs IFEval, Figure 7 shows safety vs fluency and Figure 8 shows safety vs MMLU.

D.2. In-distribution results

In Figure 9 we show in- and out-of-distribution performance side by side. In-distribution we see that **CC-Delta** achieves strong safety gains across all models, with particularly impressive performance on Qwen-2.5-7b-it (17pp safety increase with only a 0.03pp drop in utility) (Figure 2), CAA outperforms **CC-Delta** for in-distribution attacks on Gemma-2-9b-it.

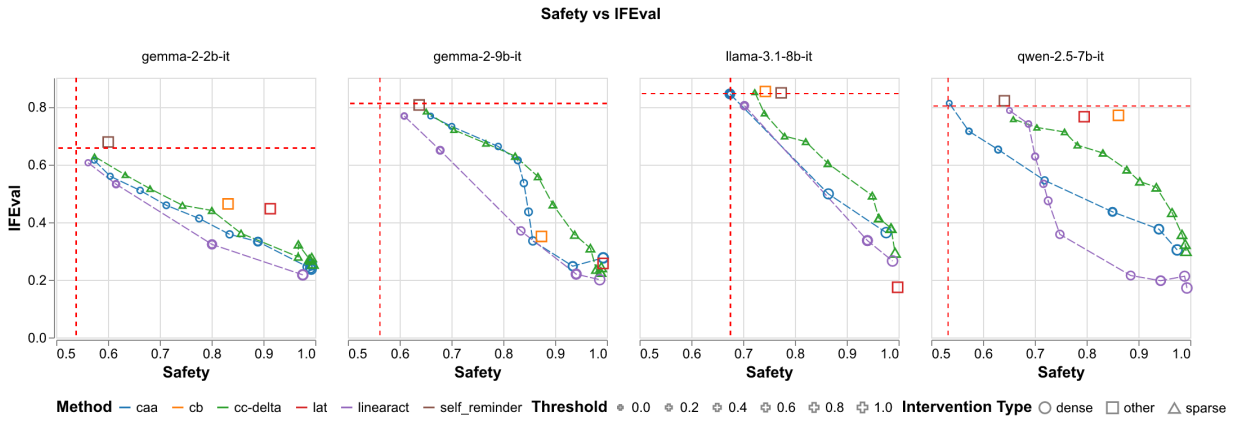

Figure 6. Safety vs. IFEval

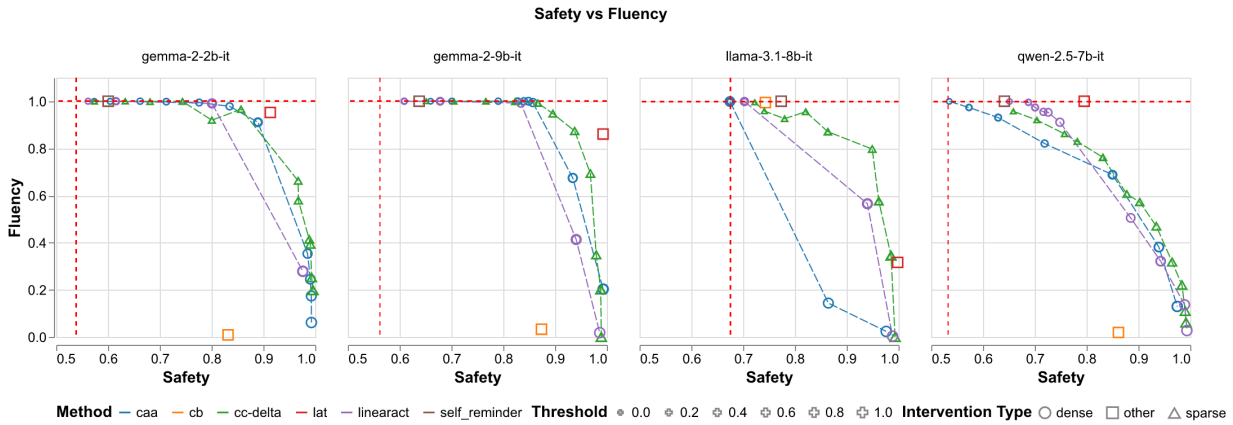

Figure 7. Safety vs. Fluency

D.3. Base Model Normalized Performance

To facilitate cross-model comparison, we normalize safety improvements by the remaining headroom to perfect safety (i.e. $\frac{\text{method}-\text{basemodel}}{1-\text{basemodel}}$), and normalize utility changes relative to the base model's utility (i.e. $\frac{\text{method}-\text{basemodel}}{\text{basemodel}}$).

Under this normalization, **CC-Delta** exhibits broadly similar tradeoff behavior across all four models (Figure 10), whereas CAA exhibits wider variance (Figure 11).

D.4. Inference Time Parameters Details

In this appendix we show how performance of **CC-Delta** varies as the two inference time parameters, number of features and steering multiplier are varied (Figure 12). We contrast this with the performance of CAA and LinearAct as the one inference time parameter they share (Figure 13), strength, varies. Having the two parameters allows **CC-Delta** much more granular access to the safety-utilty tradeoff space.

D.5. Feature Selection Ablation Details

CC-Delta selects features based on how the jailbreak context changes features of the harmful prompt within specific tokens. We perform three ablations to isolate the impact of different components of our feature selection approach (Figure 14). We run these ablations only on Llama-3.1-8b-it, as it shows the largest improvement over CAA in our main results.

In our first ablation (Diff-All), Figure 14, middle, we eliminate the token matching step and compute paired differences over mean-pooled activations of all tokens in the sequences rather than just those corresponding to the harmful request. We then apply the rest of the feature selection pipeline as in **CC-Delta**. We see large drops in MMLU score which our method was

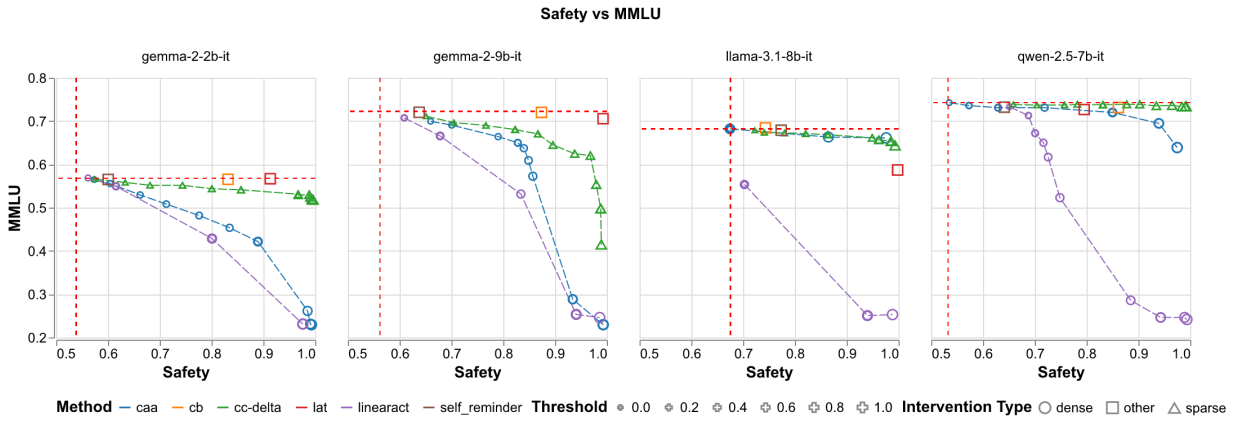

Figure 8. Safety vs. MMLU

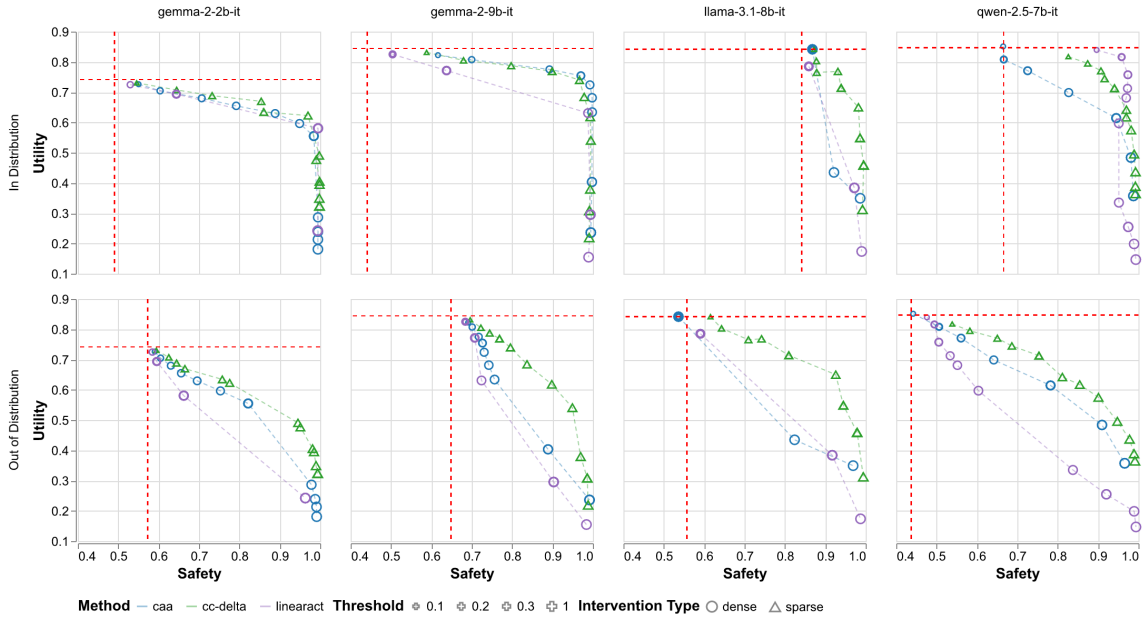

Figure 9. In-distribution vs Out-of-distribution performance of activation based steering methods.

able to avoid as faster degradation on other utility metrics.

Our second ablation (Diff-All-Magnitude), further removes the Wilcoxon-signed ranked test used to test feature diff significance. We rank features by the magnitude of the mean difference between jailbreak and harmful prompt activations. This completely destroys fluency and MMLU scores as shown in Figure 14, bottom.

Our third ablation (**CC-Delta**-Magnitude) retains token matching but removes the statistical testing and filtering phase, instead ranking candidate features only by the magnitude of their mean difference. This isolates the contribution of the statistical filtering stage: even with the benefit of token matching, removing the statistical filter substantially degrades the safety–utility tradeoff compared to full **CC-Delta** (Figure 5), confirming that the statistical filtering step is independently important.

We also investigate whether the token selection from **CC-Delta** would benefit steering in dense activation (CAA_CC in Figure 15) and find that safety is not improved when we apply the context conditioning. We suspect that in dense space, the loss of the information from the additional jailbreak tokens makes the computed vector ineffective for the task.

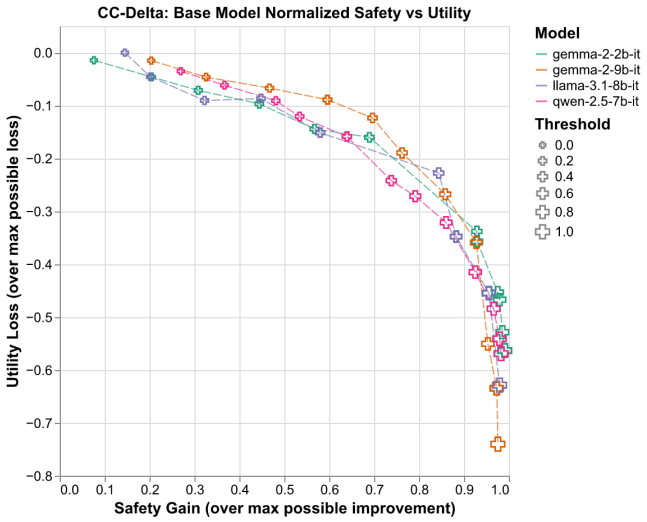

Figure 10. Normalized safety-utility curves for **CC-Delta** across models.

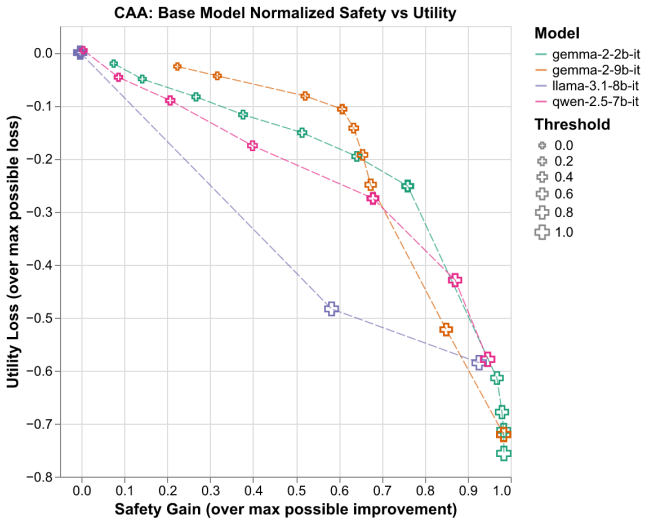

Figure 11. Normalized safety-utility curves for CAA across models.

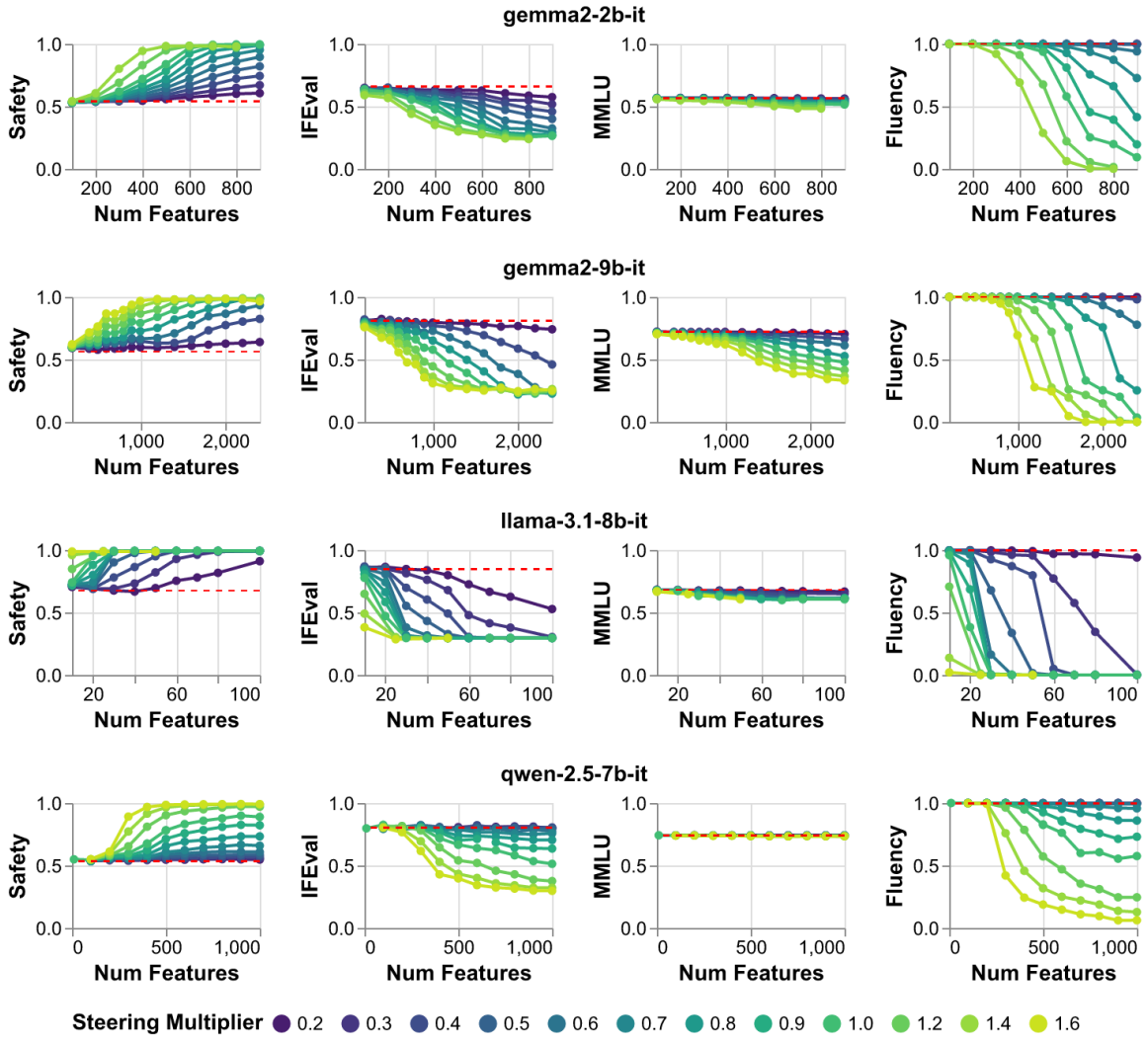

Figure 12. Effect of number of features and steering multiplier for **CC-Delta**

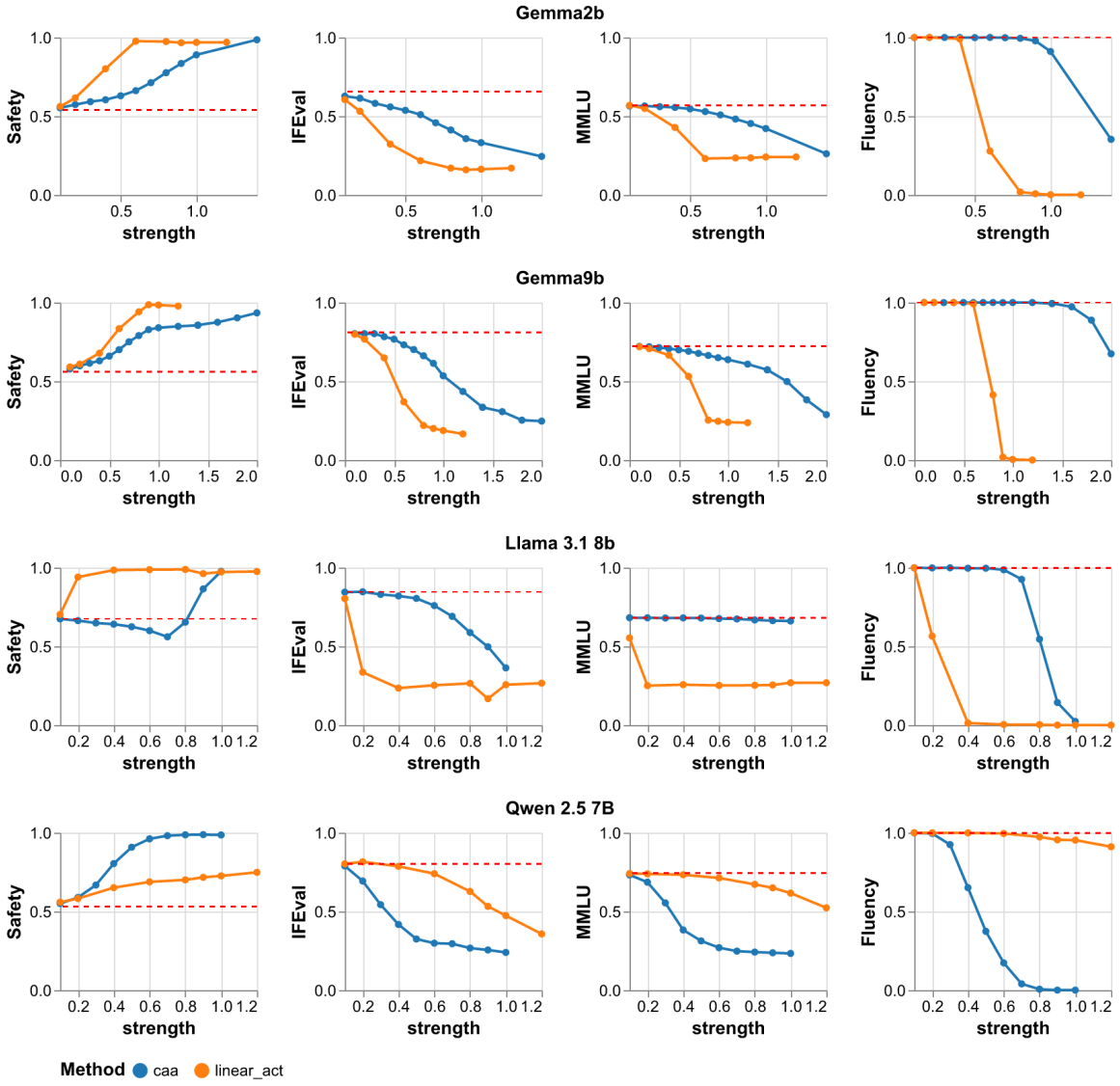

Figure 13. Effects of steering strength for CAA and LinearAcT

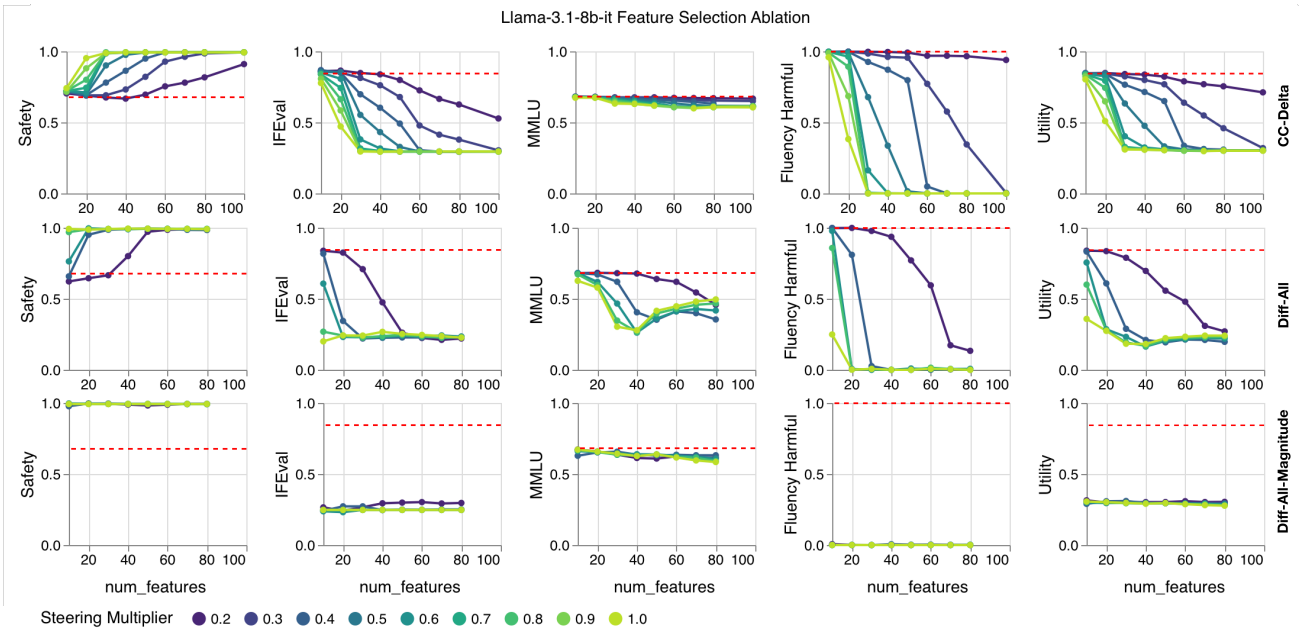

Figure 14. Ablations on feature selection components. Diff-All (middle) removes context-conditioned token selection, Diff-All-Magnitude (bottom) additionally removes our statistical ranking approach and instead ranks features by magnitude of mean differences. **CC-Delta** (top) uses context-conditioned token selection with statistical effect size ranking. The **CC-Delta**-Magnitude ablation is shown in Figure 5.

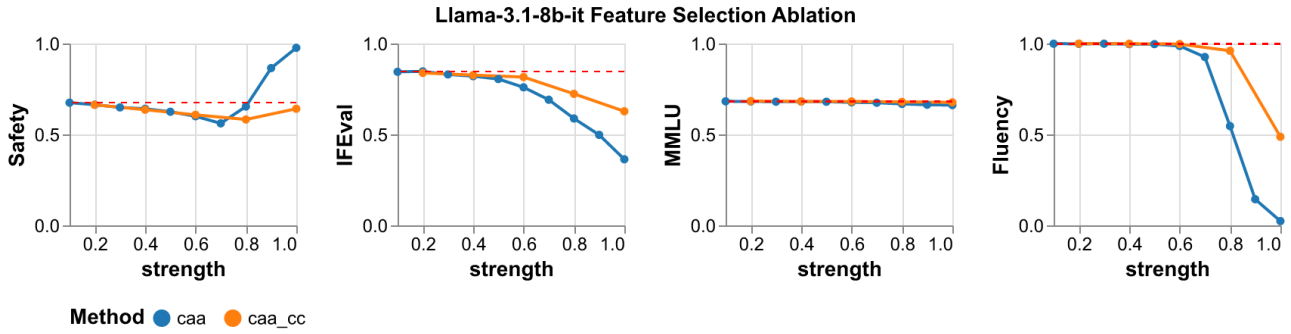

Figure 15. Applying context-conditioned token selection to CAA (caa-cc) renders it ineffective at mitigating jailbreaks

D.6. OR-Bench Over-Refusal Evaluation

To assess whether **CC-Delta** causes unwarranted refusals on benign prompts, we evaluate on OR-Bench (Cui et al., 2024), a benchmark specifically designed to measure over-refusal. We use a 20% stratified sample covering all 10 OR-Bench categories (16,072 prompts per condition), scored with the repository's LLM-based evaluator.

Figure 16 shows the safety vs. OR-Bench tradeoff for **CC-Delta**, CAA, and other baselines. The qualitative picture is consistent with our main findings: **CC-Delta** remains competitive with or better than CAA across most settings. Notably, OR-Bench compliance degrades more slowly than IFEval or Fluency as safety increases, suggesting that **CC-Delta** has relatively limited interference with benign-request compliance even when safety improves substantially. Other baselines show substantially worse safety / OR-Bench tradeoffs.

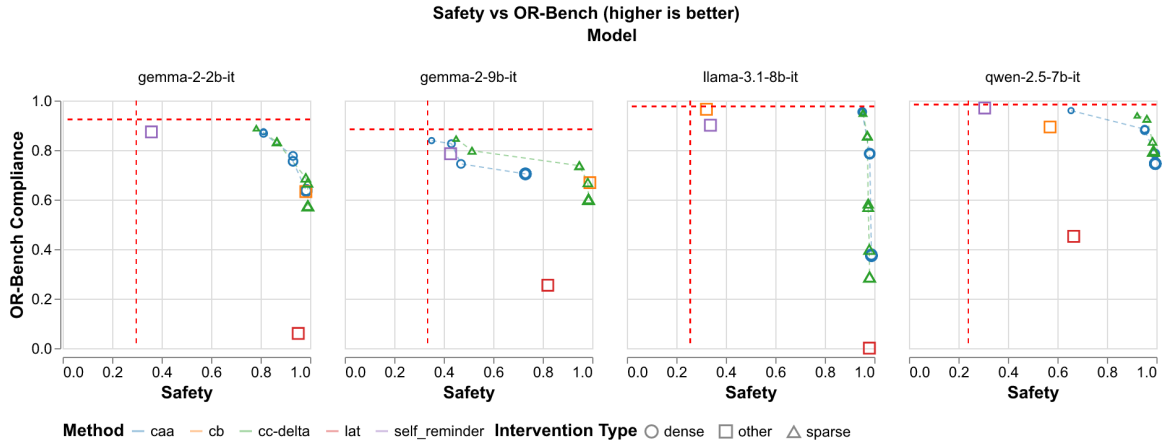

Figure 16. Safety vs. OR-Bench over-refusal score across methods and models.

D.7. PAIR Adaptive Attack Results

Table 5 reports Safety / Utility values at multiple utility-loss thresholds for **CC-Delta** and CAA under the PAIR attack (see Section 5.3 for discussion).

Table 5. Safety and utility under the PAIR attack for **CC-Delta** and CAA at multiple utility-loss thresholds. Each cell reports Safety / Utility.

Model	Method	Baseline	$\Delta \leq 0.10$	$\Delta \leq 0.25$	$\Delta \leq 0.50$	$\Delta \leq 1.00$
Gemma 2B	**CC-Delta**	.220 / .741	.296 / .704	.675 / .641	.929 / .479	.988 / .293
	CAA	.220 / .741	.244 / .705	.484 / .629	.939 / .403	.985 / .188
Gemma 9B	**CC-Delta**	.194 / .846	.252 / .818	.341 / .769	.772 / .634	.987 / .315
	CAA	.194 / .846	.218 / .807	.224 / .775	.393 / .634	.894 / .404
Llama 3.1 8B	**CC-Delta**	.173 / .845	.320 / .796	.667 / .714	.888 / .639	.998 / .300
	CAA	.173 / .845	.183 / .807	.183 / .807	.402 / .595	.982 / .210
Qwen 2.5 7B	**CC-Delta**	.173 / .848	.364 / .809	.629 / .741	.894 / .591	.989 / .424
	CAA	.173 / .848	.211 / .831	.275 / .780	.623 / .614	.992 / .193

D.8. Comparison with External Safety Classifiers

External classifier-based defenses such as guard models (Inan et al., 2023) and moderation APIs provide model-agnostic safety layers that filter inputs or outputs without modifying the target model's internal computation. To position **CC-Delta** relative to this complementary class of defenses, we evaluate the OpenAI Moderation API in both input-filtering (classifying jailbreak prompts) and output-filtering (classifying model responses) modes. Because the external classifier does not modify the target model, we report MMLU, IFEval, and Fluency from the undefended base model.

On the main jailbreak experiments (Figure 17), the Moderation API improves safety by $+0.15$–0.28 (input) and $+0.10$–0.23 (output), but **CC-Delta**'s Pareto curve extends to higher safety levels while retaining comparable utility. The gap is larger under the adaptive PAIR attack (Figure 18), where the Moderation API achieves more modest gains of $+0.17$–0.22 (input) and $+0.18$–0.24 (output), while **CC-Delta** extends substantially further along the safety axis. Table 6 reports the full results.

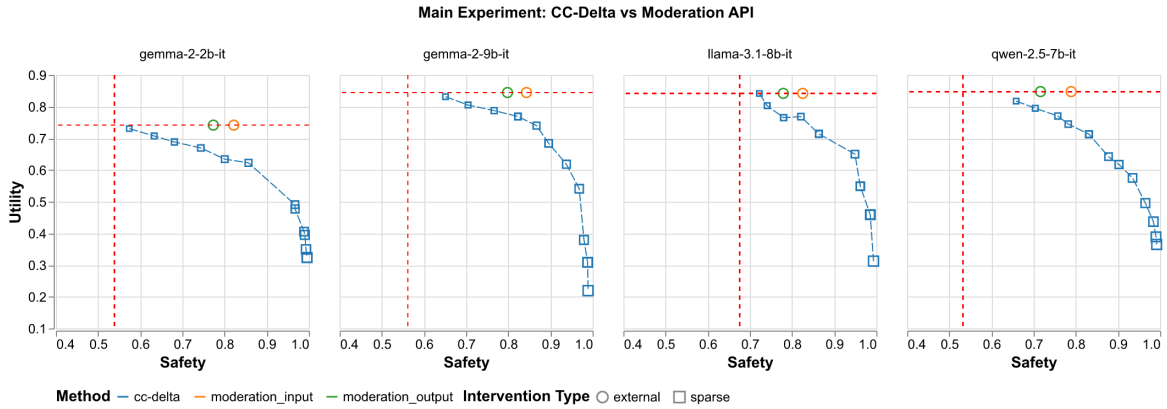

Figure 17. Safety vs. Utility for **CC-Delta** compared with the OpenAI Moderation API (input and output filtering) on main jailbreak experiments.

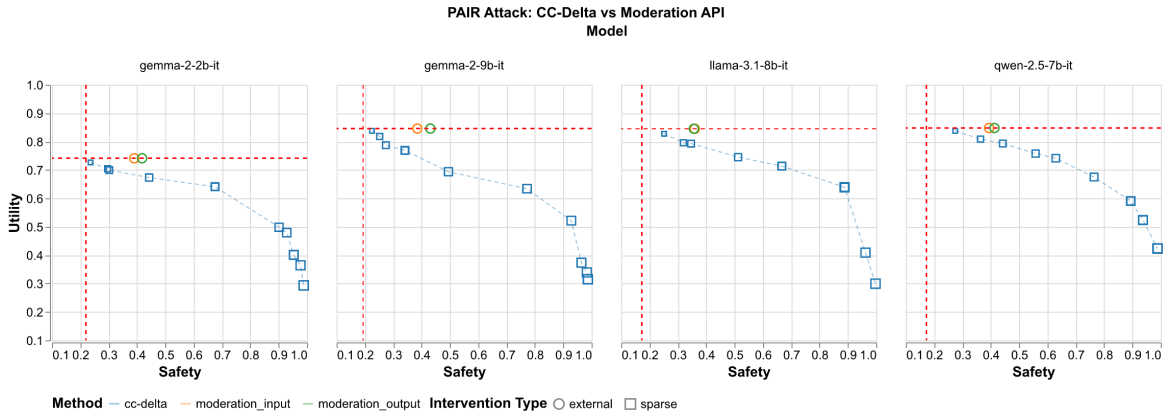

Figure 18. Safety vs. Utility for **CC-Delta** compared with the OpenAI Moderation API under the adaptive PAIR attack.

We view external classifiers and internal interventions as complementary: external classifiers provide a model-agnostic safety layer without modifying the target model's computation, while internal interventions such as **CC-Delta** reach higher-safety operating points, particularly under adaptive attacks.

Table 6. OpenAI Moderation API safety scores (input and output filtering) compared with undefended base model safety.

Attack Set	Model	Original	Input Mod.	Output Mod.
Main	Gemma 2B	0.539	0.822 +.283	0.773 +.234
	Gemma 9B	0.562	0.843 +.281	0.798 +.236
	Llama 3.1 8B	0.675	0.825 +.150	0.779 +.104
	Qwen 2.5 7B	0.533	0.789 +.256	0.716 +.184
PAIR	Gemma 2B	0.220	0.391 +.170	0.418 +.198
	Gemma 9B	0.194	0.385 +.191	0.431 +.237
	Llama 3.1 8B	0.173	0.360 +.187	0.356 +.184
	Qwen 2.5 7B	0.173	0.394 +.221	0.413 +.240

D.9. Effect of SAE Properties on Steering Quality

To investigate how SAE quality affects downstream steering performance, we evaluated 13 GemmaScope SAEs at the same intervention layer with different target sparsities. We measured both L_0 (average number of active features) and reconstruction quality (fraction of variance unexplained, FVU) on our data.

Although these SAEs span the expected sparsity–reconstruction tradeoff, we did not observe a consistent monotonic relationship between either metric alone and the downstream safety–utility tradeoff (Figure 19 and Figure 20). Our interpretation is that coarse summary statistics such as L_0 and FVU are not, by themselves, good proxies for steering quality. What appears to matter more is whether the SAE exposes useful jailbreak-relevant directions at the chosen layer. We would still expect extremely poor reconstruction or highly entangled features to hurt performance, but within the range of SAE quality we evaluated, these aggregate metrics do not reliably predict steering effectiveness.

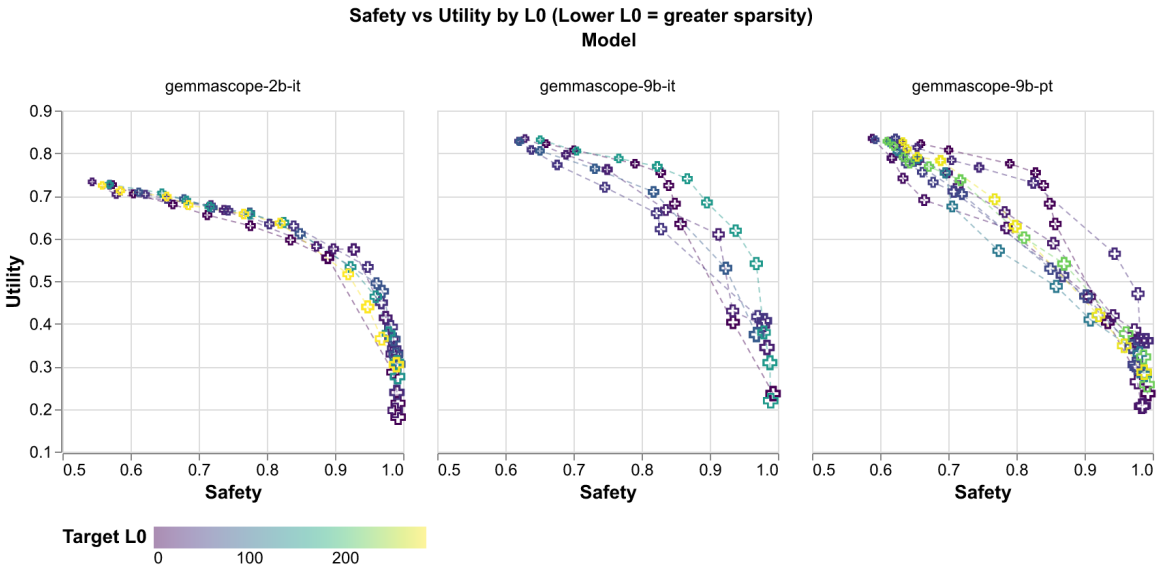

Figure 19. SAE sparsity (L_0) vs. downstream task performance across 13 GemmaScope SAEs at the same intervention layer.

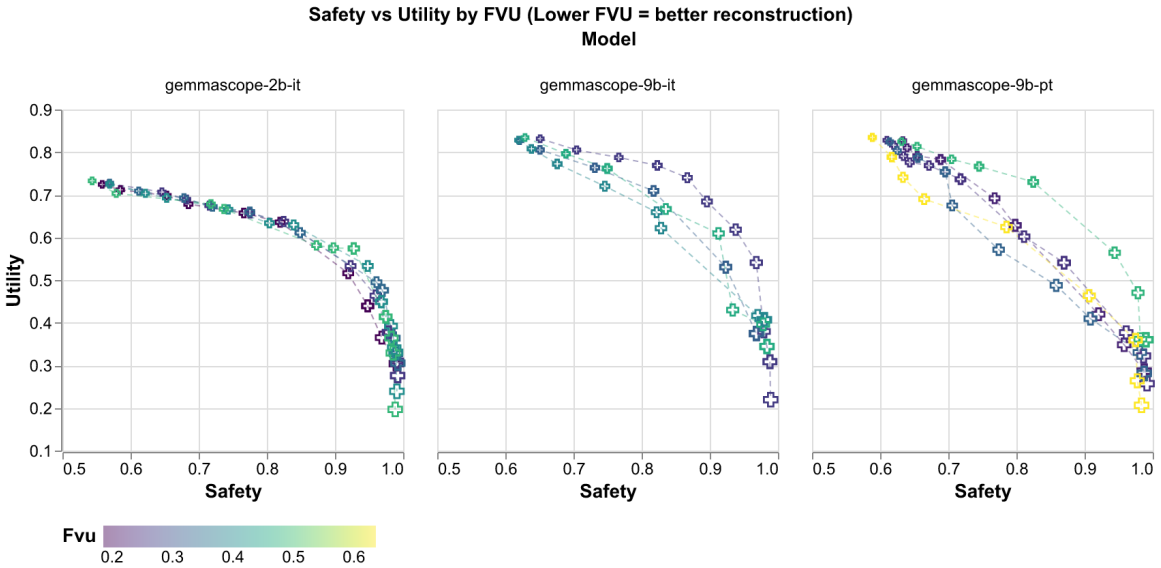

Figure 20. SAE reconstruction quality (FVU) vs. downstream task performance across 13 GemmaScope SAEs at the same intervention layer.

D.10. SAE Feature Descriptions

One of the motivating goals of decomposing model interventions using sparse autoencoders is to yield a set of sparsely activated and *interpretable features*. Sparsity itself contributes to interpretability as it yields fewer units to analyze in order to understand behavior, but in some cases also yields features that admit a compact natural language description. Because of the limitations of current auto-interpretability techniques for SAE features our method explicitly avoided selecting features based on their natural language descriptions, but we want to briefly turn to the question of how interpretable the features selected by **CC-Delta** are.

We focus on Llama-3.1-8b because of the small number of features needed to achieve the desired steering effect admits manual inspection of all the relevant features. Table 7 shows descriptions of the top 25 features along with links to their Neuronpedia pages (Lin, 2023). We provide both the Neuronpedia description (and link out to the Neuronpedia feature page) as well as descriptions generated from the same activations using Semantic Regexes (Boggust et al., 2025).

The top ranked feature, (ID 56112), frequently activates on text related to the "rights around free speech and freedom of assembly", which seems relevant however the next seems to have no discernible pattern. The third seems to activate on musicians and stories about them and at first seems surprising but a closer look at the activating snippets shows that many include references to dangerous behavior, harm or other sensitive topics.

A notable pattern is that many selected features are suppressed under jailbreak context. Among the top 25 features, all are reduced after the jailbreak is applied, and only six fire on any training samples in the jailbreak context. This suggests that, rather than introducing new features, jailbreaks often operate by suppressing features that are active in the original harmful request.

Overall we find that attempting to interpret individual SAE features as mechanistic explanations for behavior remains quite challenging. While addressing this is beyond the scope of this work, we include these feature descriptions to facilitate further analysis and community exploration. A natural next step is to design targeted interventions or controlled experiments that test what behaviors these features modulate in other contexts.

Table 7. Top 25 SAE features selected from the experiment on llama-3.1-8b-it with links to neuronpedia pages as well descriptions from neuronpedia and generated with semantic regex. "Inactive" means this feature did not fire on any samples in the dataset.

Rank	ID	Harmful Mean	Jailbreak Mean	Description (linked)	Semantic Regex
0	56112	11.922	2.729	references to legal concepts and issues related to freedom of speech and assembly	[:field legal restrictions on speech and expression:]
1	78436	11.118	Inactive	phrases and punctuation typically associated with web links or citations	[:field any_text:]
2	126619	10.987	Inactive	references to music artists and their accomplishments	[:symbol __NO_MATCH__:]{:context none:}?
3	29344	10.887	Inactive	references to health-conscious beverage options	[:field beverage_market_demand _metrics_and_trends:]
4	106228	10.869	Inactive	elements related to artistic production and expression	[:field any_span:]
5	29110	10.900	Inactive	Java classes and objects related to input and output operations	[:lexeme new:] [:field class_or_type_name:]
6	82912	10.824	Inactive	No Activations Available	No Activations Available
7	125671	10.856	Inactive	terms related to societal and economic impacts	[:field extreme_degree:]
8	128869	10.837	8.373	expressions indicating interest or involvement in various activities or subjects	[:lexeme get into:]
9	84298	10.842	Inactive	words related to web page access and viewing	No valid single Semantic Regex can be constructed: the highlighted fragments do not share a common symbol, lexeme, semantic field, or topic that appears in all examples.
10	87483	10.823	Inactive	technical terms related to permissions and access management in cloud computing	[:symbol WatchDescribeAlarmsRequest:]
11	126586	10.767	Inactive	numerical ratings associated with performances or events	[:field small_identifier_or_version_fragment:]
12	71280	9.788	3.689	specific terms and names related to various industries, especially in technology and culture	[:field foreign_term:]
13	119273	10.870	Inactive	No Activations Available	No Activations Available
14	60996	10.821	Inactive	occurrences of the word "aus" and its variations in different contexts	[:symbol Aus:]|[:symbol Auf:]|[:symbol uf:]|[:symbol erauf:]
15	75042	10.738	2.410	inquiries related to the firm's services and operations	@{:context customer_support_faq:}([:field interrogative_question_phrase:])
16	106599	10.867	Inactive	No Activations Available	No Activations Available
17	93859	10.987	Inactive	references to the Express web framework and its components	[:symbol express:]|[:symbol FastAPI:]|[:symbol chai:]|[:symbol express.Router:]|[:symbol express.response:]|[:symbol express.Router.prototype:]
18	118754	12.599	2.354	terms related to business and technology impacts, particularly those affecting employment and work dynamics	(?!)
19	76528	10.900	Inactive	patterns and structures in code or programming syntax	[:lexeme ""\)\)?\s *[{;]?"" :]
20	16449	10.857	Inactive	terms related to circularity and circular shapes	[:symbol circ:]
21	3572	11.724	9.490	references to systems and structured methodologies	[:lexeme system:]
22	57355	10.833	Inactive	instances of political discourse and discussions surrounding political strategies	(?!.).
23	77209	10.748	Inactive	technical descriptions related to mechanical or electrical systems	[:field work:]
24	40463	10.933	Inactive	No Activations Available	No Activations Available