DOES THE MODEL USE THE FEATURE? SEPARATING STEERING FROM MECHANISM IN LLMS

Anonymous authors
Paper under double-blind review

ABSTRACT

Internal features in LLMs are often interpreted as mechanisms when they track a concept and their manipulation changes a related behavior. Yet steering can push a feature far outside its natural range, where its effects need not reflect the model's own computation. We examine this inference and propose an empirical contract whose tests evaluate features at values observed on natural inputs. One test copies a feature's value from an input that shows a behavior into a matched input that does not (installation) or the reverse (removal); the other restores the feature after an upstream edit (downstream rescue). Installation measures how far the feature suffices for the behavior; removal and downstream rescue measure how much the model uses it. Applied to three kinds of representations, the two strengths separate sharply. The published unknown-entity latent strongly steers knowledge abstention, yet installing observed values from either published latent into matched prompts transfers only a small fraction of the natural known–unknown abstention contrast. Dense known–unknown directions show opposite asymmetries between installation and removal in Gemma and Llama, and how fully a released subject–verb agreement feature set reproduces and restores the behavior depends on how its values are written into the model. Tracking a concept and steering a behavior therefore do not by themselves show that the model uses a feature, and each conclusion holds only for the intervention tested.

1 INTRODUCTION

Internal features offer candidate explanations for how LLMs produce behavior. Prior work links refusal to a single direction (Arditi et al., 2024), organizes sparse features into interpretable causal graphs (Marks et al., 2025), and identifies sparse autoencoder (SAE) latents whose steering changes whether a model declines to answer questions about an entity (Ferrando et al., 2025), a behavior we call *knowledge abstention*. These results invite a mechanistic reading: if a feature tracks a concept and editing it changes the associated behavior, the model may use that feature to produce the behavior. But control is not the same as mechanism. Steering can drive a feature far beyond its *natural range*, the values it takes on natural inputs, and sufficiently large edits may recruit downstream pathways that the model does not ordinarily use. We therefore ask: *when does feature-level control support a mechanistic interpretation of natural computation?*

We study this question with an *empirical contract* that distinguishes association, control, sufficiency, and use (Table 1). Association and control capture the familiar observations that a feature tracks a concept and that editing it changes behavior. The stronger claims ask whether the feature's natural values reproduce the behavior (*sufficiency*) and whether the model's own computation depends on the feature (*use*). We test both at values observed on natural inputs (Figure 1). In an *interchange* test (Geiger et al., 2021), paired inputs from two conditions exchange their feature values: *installation* transfers the value associated with the target behavior, while *removal* performs the reverse. In *downstream rescue*, we edit the model upstream, restore the feature downstream, and measure how much behavior returns. Installation probes sufficiency; removal and rescue probe use.

Our main audit focuses on the published entity-recognition latents of Ferrando et al. (2025). We reproduce their separation of known and unknown entities and the strong steering effect of the unknown-entity latent. Yet setting the latent to a value within its natural range barely changes knowledge abstention; the behavior increases only when the latent is pushed beyond that range (Fig-

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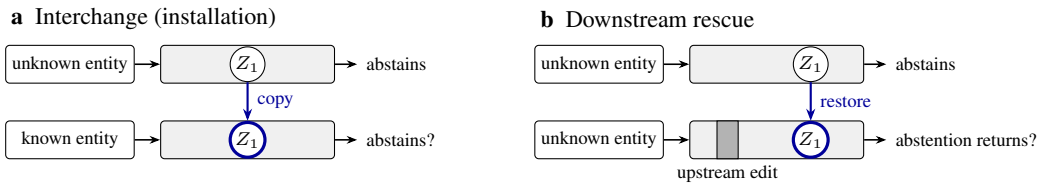

Figure 1: The two tests of the empirical contract, shown for entity familiarity and knowledge abstention. Each row is a forward pass; circles mark the feature's value at its site. *a:* Installation copies the feature's natural value Z_1 from the input that shows the behavior (the target) into a matched input that does not (the comparison) and asks whether behavior moves to the target level; removal copies Z_0 the other way. *b:* Downstream rescue applies an upstream edit that changes the feature and the behavior, restores the feature's natural value downstream while the edit stays active, and measures how much of the behavioral change is reversed.

Table 1: Four feature claims and the evidence used to assess them.

Claim	**Usual evidence**	**Contract evidence**
Association	Development-set separation	Replication on held-out inputs with the site and labels fixed.
Control	Steering at one strength	Predicted effect at a verified achieved value, compared with the natural range.
Sufficiency	Nonzero installation effect	Sufficiency strength: the fraction of the natural contrast reproduced by installing matched natural values.
Use	Nonzero removal effect	Use strength: the larger of the fraction of the contrast eliminated by removal and the fraction of an upstream effect reversed by downstream rescue.

ure 2). Likewise, installing the known-entity latent's common-name value into a prompt that names the same entity by a rare alias does not recover the accuracy gain of the common name. An independently fitted refusal direction serves as a positive control, showing that our tests detect effects at natural values when they are present. To separate a failure of the SAE basis from a failure of the underlying concept, we also test dense known–unknown directions defined by class-mean differences. Their behavior is asymmetric across models: Llama shows strong installation but weak removal and rescue, whereas Gemma shows stronger removal but weak installation and rescue. By contrast, a released subject–verb agreement feature set spanning multiple layers shows high sufficiency and use strengths on held-out vocabulary when its values are written through the SAE decoders (the *decoder update*).

The same feature set shows why the update rule, the procedure used to write a value into the model, is part of the intervention claim. Both the decoder update and the encoder-constrained update, which matches the requested feature values more closely, recover the preferred verb on almost all pairs. Yet the decoder update yields a much higher sufficiency strength and stronger rescue: downstream layers read the residual stream, not the encoder's output, and the two updates change the residual stream differently. The entity results make the same point about the representation: an SAE latent and a dense direction with the same semantic label behave differently under the same tests. The contract therefore specifies the representation, site, edited tokens, update rule and behavioral measure together.

Our contributions are:

- **An empirical contract for feature claims** that measures the strength of sufficiency and use at values observed on natural inputs (Section 4).
- **An audit of entity-familiarity representations**: the published SAE latents steer knowledge abstention, but paired interchange transfers only a small fraction of the natural known–unknown abstention contrast; dense directions dissociate installation from removal (Sections 5.1–5.3).

- **A positive case that depends on the update rule**: the agreement feature set of Marks et al. (2025) reaches its highest sufficiency and rescue only under the decoder update (Sections 5.3 and 5.4).

2 Related work

SAE features and semantic interpretations. Sparse autoencoders decompose transformer activations into sparse learned features, many with interpretable semantic descriptions (Cunningham et al., 2024; Bricken et al., 2023; Templeton et al., 2024). Resources such as Gemma Scope provide pretrained JumpReLU dictionaries for feature-level analysis (Lieberum et al., 2024; Rajamanoharan et al., 2024). Ferrando et al. (2025) identify entity-recognition latents that distinguish known from unknown entities and connect them to knowledge abstention and factual recall through steering, weight orthogonalization, and activation patching. Other work probes feature interpretations through behavioral falsification (Ma et al., 2026), and Paulo & Belrose (2026) find that feature identity can vary across retraining seeds, especially for TopK dictionaries. Entity-feature audits further separate detection from control: fabricated-entity detection and refusal steering can occupy distinct directions (Galeone et al., 2026), while a Qwen replication finds no calibration gain from single-feature steering and increased hallucination after multi-feature ablation (Vicentino, 2026). Cui et al. (2026) recover suppressed behavior through residual-space edits while holding targeted SAE features fixed. Makelov et al. (2025) benchmark SAE disentanglement and control on indirect-object identification against supervised task-specific dictionaries. Our audit is similarly task-grounded, but tests fixed candidate features through installation, removal and rescue at values observed on natural inputs.

Steering, activation patching, and intervention validity. Steering vectors can control behavior across forced-choice tasks and open-ended traits (Rimsky et al., 2024; Chen et al., 2025), though SAE steering may underperform simple prompting (Wu et al., 2025). For refusal, Arditi et al. (2024) derive a harmful–harmless direction and control refusal through addition and directional ablation. Later work identifies refusal concept cones and geometrically distinct directions with similar refusal–over-refusal trade-offs (Wollschläger et al., 2025; Joad et al., 2026). We distinguish a representation from the edit used to intervene on it: addition, directional ablation, and replacement with an observed value are different interventions. Interchange interventions replace internal states with values from another input to test causal abstractions and trace computations (Geiger et al., 2021; 2025; Vig et al., 2020; Meng et al., 2022), and have been used for attribute disentanglement (Huang et al., 2024), interpretation validity (Li et al., 2026), and steerable causal subspaces (Bao et al., 2026). We apply interchange to fixed candidate representations and compare the installed behavior with that of the matched natural input. Our downstream-rescue test follows denoising activation patching (Heimersheim & Nanda, 2024), restoring the candidate state while keeping the upstream edit active. Patching conclusions can depend on the metric, corruption scheme, and ablation rule (Zhang & Nanda, 2024; Miller et al., 2024); causal localization also need not identify the best sites for knowledge editing (Hase et al., 2023), and subspace patching can activate dormant pathways rather than restore the model's usual computation (Makelov et al., 2024). Finally, feature interventions can exceed typical activation levels (Templeton et al., 2024; Ameisen et al., 2025) or reach residual states not produced by any prompt (Mishra et al., 2026). We therefore measure how far steering moves feature values beyond their observed natural range.

Behavioral dependence and causal claims. Amnesic probing tests behavioral dependence by removing decodable information and measuring the resulting behavioral change (Elazar et al., 2021). Work on grammatical number uses usage probes (Lasri et al., 2022), causal mediation (Finlayson et al., 2021), and counterfactual interventions (Ravfogel et al., 2021) to test which representations contribute to subject–verb agreement; we use the released agreement annotations of Marks et al. (2025) as a candidate positive case. Joshi et al. (2026) organize mechanistic interpretations within a causal hierarchy, and Lin & Liu (2026) emphasize the assumptions required for causal validation. Our empirical contract separates association, control, sufficiency and use, and tests the last two only at values observed on natural inputs.

3 BACKGROUND: THE AUDITED FEATURES

Entity-recognition latents. Ferrando et al. (2025) construct a Wikidata dataset of basketball players, movies, cities, and songs and prompt the Gemma 2 2B base model to complete their attributes, e.g., "The movie 12 Angry Men was directed by". An entity is *known* if the model answers at least two attributes correctly and *unknown* if it answers all incorrectly; intermediate cases are discarded. At the entity's last token, which we call the *entity token*, they select latents from the Gemma Scope dictionary for Gemma 2 2B whose firing rates best separate known from unknown entities across all four types. As in their steering experiments, we audit the resulting known-entity latent L13/7957 and unknown-entity latent L15/11898 in Gemma 2 2B-IT, using the released entities and labels.

Knowledge abstention and steering. For behavioral evaluation, these completions become questions such as "Who directed the movie 12 Angry Men?". We use *knowledge abstention* for responses that give no substantive answer because they express uncertainty, claim inability, decline, or reject the entity or premise. It differs from refusing harmful requests and from instruction refusal, which our positive control measures (Section 5). Ferrando et al. (2025) identify such responses by string matching and steer by adding the latent decoder direction d_j to the residual stream, $r \leftarrow r + \alpha d_j$, at the entity token and subsequent end-of-instruction tokens, with α roughly twice the residual-stream norm. Steering with the unknown-entity latent causes near-universal abstention on unknown-entity questions, while the known-entity latent induces hallucination about a non-existent player the model would otherwise decline to answer.

Subject–verb agreement features. Marks et al. (2025) annotate SAE features in Pythia-70M-deduped that mediate subject–verb agreement, where the model must prefer the verb form matching the subject's grammatical number, e.g., "is" after the prefix "The nurse" and "are" after "The nurses". We treat 147 annotated features across six residual-stream sites as one feature set. Because the released test split reuses the vocabulary used for annotation, we evaluate on newly constructed nouns (Appendix C). Table 2 summarizes all audited representations.

4 THE EMPIRICAL CONTRACT AND ITS TESTS

Because sufficiency and use concern the model's own computation, the contract tests them only by setting the feature to values observed on natural inputs, and asks whether these edits reproduce the natural difference between conditions, not merely whether behavior is sensitive to them. A candidate feature state $Z(x)$ is the value of a single latent or direction at a specified site, or the joint state of a feature set across several sites; B is the behavior it is meant to explain. The four claims of the contract (Table 1) ask progressively more of the feature: the usual evidence for association and control is that the feature separates the two conditions and that steering it changes B, and the contract adds the requirements in the last column of Table 1. Each claim is measured by its own test, and a weak result limits the evidence for that claim without ruling out other causal roles of the feature.

4.1 WHAT WE ESTIMATE

Each item e pairs a comparison input c_0 with a target input c_1 on which B is expected to be higher. In the entity task, c_1 asks about an entity labeled unknown and c_0 about a matched entity labeled known, using the same prompt type; B is knowledge abstention. In the agreement task, c_0 and c_1 differ only in the subject's grammatical number (plural in c_0, singular in c_1), and $B = \ell(v_{\mathrm{sg}}) - \ell(v_{\mathrm{pl}})$ is the difference between the logits ℓ of the singular and plural verb forms. Let $Z_j = Z(c_j)$ be the feature's natural value on each input, and let $Y(c, z)$ be the behavior on input c when the update rule sets the feature to z; for a multi-site feature set, z is the tuple of requested site values, and the update rule writes each component at its site as the forward pass reaches it. The natural contrast is $\Delta_{\mathrm{nat}} = \mathbb{E}[Y(c_1, Z_1) - Y(c_0, Z_0)]$, with intervals clustered by paired entity or noun group.

Interchange. Installation runs the comparison input with the target's value, $Y(c_0, Z_1)$, and removal runs the target input with the comparison's value, $Y(c_1, Z_0)$. We express both as fractions of the natural contrast:

$$\rho_{\mathrm{install}} = \frac{\mathbb{E}[Y(c_0, Z_1) - Y(c_0, Z_0)]}{\Delta_{\mathrm{nat}}}, \qquad \rho_{\mathrm{remove}} = \frac{\mathbb{E}[Y(c_1, Z_1) - Y(c_1, Z_0)]}{\Delta_{\mathrm{nat}}}.$$

Table 2: Representations audited in this work; Section 5 adds a refusal direction as a positive control.

Representation	Model	Site	Origin
Known- and unknown-entity latents (L13/7957, L15/11898)	Gemma 2 2B-IT	entity token, layers 13 and 15	Ferrando et al. (2025)
Known–unknown direction	Gemma 2 2B-IT	entity token, layer 15	class-mean difference fit on disjoint entities
Known–unknown direction	Llama 3.1 8B-Instruct	entity token, layer 15	class-mean difference fit on disjoint entities
Agreement feature set (147 features)	Pythia-70M-deduped	final prefix token, six sites	annotations of Marks et al. (2025)

We take ρ_{install} as the *sufficiency strength*: a value of 1 means that installing the target's natural value reproduces the target's mean behavior, and the remaining installation gap, $\mathbb{E}[Y(c_1, Z_1) - Y(c_0, Z_1)] = (1 - \rho_{\mathrm{install}})\Delta_{\mathrm{nat}}$, is the part of the contrast the feature does not carry. As sensitivity analyses, installation and removal can also set the feature to an observed class mean instead of the matched value.

Downstream rescue. Rescue applies an upstream edit that changes both Z and B on the target input, then restores the feature to its natural value downstream while the edit remains active. With Y_U the outcome under the upstream edit alone and Y_{U+R} the outcome after restoration, $\rho_{\mathrm{rescue}} = -\mathbb{E}[Y_{U+R} - Y_U]/\mathbb{E}[Y_U - Y(c_1, Z_1)]$ is the fraction of the upstream effect that restoration reverses. Removal asks whether behavior depends on the feature's natural value, and rescue asks whether an upstream effect on behavior passes through the feature. Each is sufficient evidence of use but neither is necessary: when several components carry the same information, removing one leaves behavior intact while restoring one recovers it, and when several components are jointly required, the reverse holds (Heimersheim & Nanda, 2024). We therefore take the larger of ρ_{remove} and ρ_{rescue} as the *use strength*, and report every ratio with its 95% interval rather than thresholding it.

Update rules. Both strengths are conditional on the update rule. For SAE features S with encoder output $a = \mathrm{Enc}(r)$ and decoder columns $W_{\mathrm{dec},S}$, the *decoder update* writes the requested values $a^\star_S$ along the decoder columns, and for a dense direction v with requested projection $q^\star$ we set the projection directly:

$$r' = r + W_{\mathrm{dec},S}\,(a^\star_S - a_S), \qquad r' = r + \frac{(q^\star - v^\top r)\,v}{\|v\|_2^2}.$$

The paired writes for individual Gemma latents use the same gain-corrected setter as the dose study (Appendix B.1); the feature-set decoder update above is unchanged. For L15/11898, the residual write along d_j scales the requested preactivation change by $1/\hat{g}_j \approx 3.5$. The requested value is observed on a donor input in the encoder readout; the edited residual need not be a donor-observed state. Because re-encoding r' need not return $a^\star_S$, the *encoder-constrained update* instead solves for a residual change δ whose re-encoded values match the request, $\max_{k\in S} |\,\mathrm{Enc}_k(r+\delta) - a^\star_k| \le 10^{-3}$; we report the two feature-set updates separately. For a dense direction, we set the projection directly rather than write through SAE decoders, which would change large residual components orthogonal to the direction (Appendix C). We run no-op controls and report achieved values after re-encoding; we report no strength for an edit whose achieved value falls outside a preset tolerance of the request.

Scope. The subspace-patching illusion of Makelov et al. (2024) arises within MLP hidden activations, where it exploits the nullspace of the MLP output projection. Our edits target residual-stream representations, a location they argue is less prone to such illusions, so their construction is not a direct counterexample to these tests. Natural feature values still need not produce naturally realizable joint residual states, so a high strength is evidence under the specified representation, sites, edited tokens and update rule, not a general guarantee of mechanistic identification.

5 Applying the empirical contract to published features

Setup. We intervene on Gemma 2 2B-IT, Llama 3.1 8B-Instruct and Pythia-70M-deduped, generating open-ended responses from Gemma and Llama greedily. Features, sites, update rules, targets

and measures are fixed on development data before confirmation runs on held-out data (Appendices B and C), which also give the datasets, hardware, software and intervention settings. We run the tests of Section 4.1 only when the interval for Δ_{nat} excludes zero.

Labels. Responses to entity questions are labeled by OpenAI `gpt-5.6-terra` under a fixed six-category rubric: explicit refusal, invalid entity or premise, knowledge uncertainty and claimed inability count as knowledge abstention, whereas substantive answers and other responses do not. On 574 responses annotated independently by two humans, these labels reach a balanced accuracy of 0.94 $[0.92, 0.96]$ for knowledge abstention (Appendix A). A Qwen2.5-3B-Instruct judge with fixed prompts (the *Qwen judge*) scores instruction refusal in the refusal control and a few sensitivity analyses.

Section 5.1 reproduces the usual evidence for association and control, and Section 5.2 tests the latents at values within and far beyond their natural range. Section 5.3 applies interchange and downstream rescue, and Section 5.4 varies the update rule and the edited tokens.

5.1 The published latents retain association and strong steering

We begin with the evidence on which the published interpretation rests. On the publication's held-out test split of 800 entities, the known-entity latent L13/7957 and the unknown-entity latent L15/11898 separate known from unknown entities with macro areas under the ROC curve (AUROCs) of 0.874 and 0.745. We then apply the published steering to the unknown-entity latent at $\alpha = 400$, the lower end of the reported 400–550 range, from the entity token to the end of the prompt. On 400 unknown-entity questions, steering raises knowledge abstention from 33.0% to 79.0%, a paired change of $+46.0\,\mathrm{pp}$ $[40.5, 51.5]$, with an increase for every entity type (Appendix A).

5.2 The latents barely change behavior within their natural range

Steering shows that behavior is sensitive to an edit, not that the model relies on the values the feature takes naturally. We therefore set the unknown-entity latent at the entity token only to one of two targets: a natural target near the 95th percentile of its unedited activations, and a high target at the value the published steering reaches, beyond every unedited activation. On 400 new unknown-entity questions, we compare knowledge abstention under each target with the unedited baseline; the achieved activations match the requests (Appendix B.1).

With the feature, site, token, update rule and prompts held fixed, only moving the latent beyond its natural range clearly changes behavior (Figure 2). The natural target changes knowledge abstention by only $+1.5\,\mathrm{pp}$ $[-1.2, 4.2]$, whereas the high target raises it by $+12.0\,\mathrm{pp}$ and exceeds the natural target by $+10.5\,\mathrm{pp}$ $[6.4, 14.6]$.

A natural input change exposes the same failure in the known-entity latent. The same question can name an entity in more than one way, as in "What genre is *Battlefield Play4Free*?" versus "What genre is *BFP4F*?" On 500 held-out alias pairs, asking with the entity's common name rather than a rare alias raises factual accuracy by $11.2\,\mathrm{pp}$ $[7.6, 14.8]$, and common names also raise the known-entity latent. If the latent carried the accuracy gain, installing its common-name value in the rare-name prompt should recover the gain. Copying the full residual state at the same site recovers the gain, changing accuracy by $10.6\,\mathrm{pp}$ $[7.2, 14.0]$, but copying only the latent's value changes it by $-0.2\,\mathrm{pp}$ $[-2.0, 1.6]$ (Appendix B).

As a positive control, a refusal direction fit following Arditi et al. (2024) shows that an edit within the natural range can change behavior: setting its projection to the refusal-class mean raises instruction refusal by $+29.0\,\mathrm{pp}$ $[18, 39]$ on 100 held-out prompts (Appendix B).

5.3 Installation, removal and rescue dissociate across representations

On matched known–unknown questions, paired interchange with the published Gemma latents transfers 0.12 of the natural knowledge-abstention contrast for L15/11898 and 0.05 for L13/7957 under installation; removal eliminates 0.07 and 0.20, respectively (Table 3, Figure 3). None of the four paired-effect intervals excludes zero. Rescue was not run for either latent, so their use strength is known only to be at least their removal fraction. To show what high sufficiency and use strengths

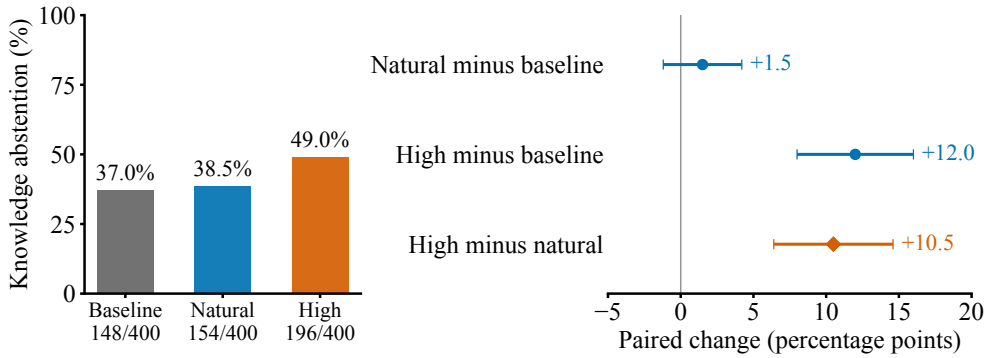

Figure 2: Only the high target, beyond every unedited activation, clearly raises knowledge abstention. The unknown-entity latent is left unedited (baseline) or set to the natural or the high target on 400 new unknown-entity questions. Left: abstention counts and rates. Right: paired changes with 95% intervals.

look like, we apply interchange and rescue to the released agreement feature set on held-out nouns; to test whether these small effects reflect the SAE basis rather than the familiarity concept, we apply them to Gemma and Llama known–unknown directions (Section 4.1). Both directions use the last entity token, matching the readout site of Ferrando et al. (2025) in Gemma and Llama.

Pairs and upstream edits. For the agreement feature set, singular and plural prefixes from 58 held-out noun groups form 232 pairs. For the directions, known entities are matched to unknown entities of the same prompt type, yielding 400 Llama and 148 Gemma pairs, and interchange copies each example's observed projection to its match. The published Gemma latents use the same 148 pairs. For rescue, the agreement upstream edit modifies 60 annotated embedding features upstream of all six feature-set sites. For the directions, the upstream edit sets the projection of unknown prompts on an upstream direction to the known-class mean at the entity token (Gemma: layer 8; Llama: development-selected layer 12; Appendix C).

Table 3: Sufficiency and use strengths. Entries are fractions of each natural contrast; the sufficiency strength is ρ_{install}, and the use strength is the larger of ρ_{remove} and ρ_{rescue}. Figure 3 shows 95% intervals; Appendix C reports exact intervals and other diagnostics.

	Sufficiency	Use		
Representation	strength ρ_{install}	removal ρ_{remove}	rescue ρ_{rescue}	strength
Agreement feature set, decoder	0.946	0.951	0.877	0.951
Agreement feature set, encoder-constrained	0.799	0.981	0.560	0.981
Llama direction	0.89	0.07	0.26	0.26
Gemma direction	0.27	0.61	0.09	0.61
Gemma latent L15/11898	0.122	0.073	—	≥ 0.073
Gemma latent L13/7957	0.049	0.195	—	≥ 0.195

Natural contrasts: agreement feature set 7.32 verb-logit units; Llama $+44.75$ pp $(179/400)$; Gemma $+27.70$ pp $(41/148)$.

Agreement feature set. Written through its SAE decoders, the feature set nearly reproduces both natural conditions (Table 3). Installation and removal each account for about 0.95 of the natural contrast, and downstream restoration reverses 0.88 of the upstream effect. Both strengths are far above those of the entity representations.

Llama direction. Installation transfers 0.89 of the natural contrast in knowledge abstention, a sufficiency strength close to that of the agreement feature set. Removal eliminates only 0.07, however, and downstream restoration reverses 0.26 of the upstream effect, so the use strength is low (0.26). The direction's observed value nearly suffices to produce the target behavior, yet behavior barely depends on it at this site.

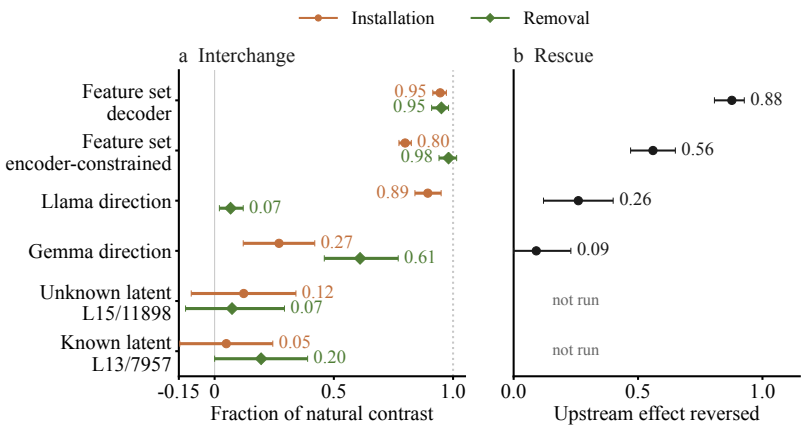

Figure 3: Interchange and rescue across representations. *a:* Fractions of the natural contrast transferred by installation and eliminated by removal (95% intervals; dotted line: full contrast). *b:* Fraction of the upstream effect reversed (95% intervals). The two feature-set rows use the same 58 noun groups and upstream edit, changing only the update rule. Both directions use the entity token. Rescue was not run for the two Gemma latents.

Gemma direction. Gemma shows the opposite asymmetry. At the entity token, removal eliminates 0.61 of the natural contrast, but installation transfers only 0.27, and restoring the direction downstream reverses only 0.09 of the upstream effect, so its use strength (0.61) exceeds its sufficiency strength. Knowledge abstention at this site is sensitive to removal, but the direction's observed value is not enough to reproduce the target behavior, and the upstream edit acts mostly through other routes.

5.4 The intervention claim depends on the update rule and edited tokens

A feature value can be written into the model in more than one way, and the ways differ in what else they change. For the agreement feature set, matching the requested feature values more exactly does not make the behavior more faithful. After re-encoding, the encoder-constrained update matches the requested values several orders of magnitude more closely than the decoder update and recovers the target verb on about as many pairs (Appendix C), yet the decoder update yields a higher sufficiency strength and stronger rescue. Removal, and with it the use strength, is nearly invariant to the update rule (0.951 versus 0.981), whereas installation (0.946 versus 0.799) and especially rescue (0.877 versus 0.560) are not (Table 3).

The refusal control shows that the edited tokens matter as well (Table 4). Zeroing the direction's projection at one site and token lowers refusal far less than ablating the direction at every layer and position, and removal at that site also lowers refusal.

Table 4: Removal at one site and token lowers refusal, whereas ablation at every layer and position suppresses it much more. The same refusal direction and 100 prompts throughout; instruction refusal is scored by the Qwen judge, and brackets are 95% intervals.

Edit	Scope	Change in refusal (pp)
Removal (projection set to the answer-class mean)	One site and token	-6.0 $[-11, -2]$
Projection set to zero	One site and token	-5.0 $[-10, -1]$
Directional ablation	All layers and positions	-45.0 $[-55, -35]$

6 Discussion

Why is published steering stronger than paired interchange? Steering and interchange ask different questions. The published steering adds about twice the residual-stream norm along the decoder direction and reaches activations far outside the natural range (Section 5.2). An edit of

that size can change knowledge abstention through any downstream computation that is sensitive to the direction, including computations that natural variation in the latent never engages. Interchange asks instead whether values observed on natural inputs carry the behavioral difference; the published latents transfer little of it, with modest removal for the known-entity latent. The dissociation parallels the gap between localization and editing reported by Hase et al. (2023) and the dormant pathways of Makelov et al. (2024): an intervention can succeed without identifying the representation the model uses. Studies that validate a feature interpretation by steering therefore test control, not sufficiency or use.

What do the asymmetries of the dense directions show? Installation and removal can dissociate either way, so sufficiency and use must be tested separately. The Llama direction nearly suffices, yet removing it at the entity token barely lowers knowledge abstention; Gemma shows the opposite asymmetry, and downstream rescue is weak in both. Previous ablation studies find that later components can compensate for edited attention layers or heads (McGrath et al., 2023; Rushing & Nanda, 2024). Similar compensation could make Llama's 0.07 removal effect and the weak rescues in both models understate the directions' contribution. The refusal direction likewise installs refusal at one token, but removal there suppresses it weakly, whereas ablation at every layer and position does (Arditi et al., 2024). A single-token edit thus probes one location of a computation that may span tokens and layers.

Why does the update rule change the result? The two feature-set updates request the same values but change different residual-stream components. Downstream layers read the residual stream, not the SAE encoder's output, so a write whose re-encoded values match the request more closely need not reproduce the natural computation more closely: the encoder-constrained update is the more accurate in feature space and the less accurate in behavior[1] (Section 5.4).

7 Conclusion

Does the model use the feature? Association and control alone cannot answer this. We reproduce the known–unknown separation and the strong steering effect of the published entity-recognition latents. Under paired interchange, however, these single latents carry only a small fraction of the natural known–unknown abstention contrast, with modest asymmetric removal for the known-entity latent. Dense known–unknown directions show opposite asymmetries between installation and removal in the two models, and the agreement feature set reaches its highest sufficiency and rescue only under the decoder update. Feature claims should therefore report the values steering reaches relative to the natural range, measure sufficiency by installing values observed on natural inputs, measure use through removal and downstream rescue, and specify the representation, site, edited tokens, update rule and behavioral measure together.

Reproducibility statement

An accompanying artifact contains the input sets, raw generations, judge outputs, intervention diagnostics, analysis code and figure-generation scripts needed to reproduce the reported results. The complete experimental codebase will be released upon publication.

AI use statement

We used Anthropic Claude and OpenAI GPT/Codex systems for literature discovery, code implementation and review, analysis support, and paper polishing. We verified cited sources and scientific claims, reviewed generated code and reproduced the reported analyses and software tests.

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A DIRECTION FITTING, REFUSAL CONTROL AND LABELING

Direction fitting and sites. Ferrando et al. (2025) read the final token of each entity; their top Llama 3.1 8B unknown-entity latent is at layer 15. Our known–unknown directions are separately fitted class-mean differences on disjoint entities at that layer and token in both models (Table 2).

Labels. We use OpenAI `gpt-5.6-terra` only as a response classifier; it does not generate any task responses. The adjudicator receives the question, reference answer and generated response, but not the intervention condition, model condition, baseline-versus-edited status or expected label. Reasoning is disabled, sampling is off, temperature is 0 where supported by the API and the maximum output length is 32 tokens. A structured output schema restricts the response to one of six labels. An invalid output is retried once with the same prompt and otherwise mapped to `OTHER`. The adjudicator assigns one of six categories: substantive answer, explicit refusal, invalid entity or premise, knowledge uncertainty, claimed inability, or other. On entity questions, explicit refusal, invalid entity or premise, knowledge uncertainty and claimed inability count as knowledge abstention when the response supplies no substantive answer. Safety and instruction refusal use separate binary mappings. Identical question–reference–response triples are adjudicated once and share that label.

Rubric development and human comparison. The rubric was developed on the 88-question dose development set and its responses, together with a separate set of 574 responses annotated by two humans blind to intervention condition. Against the human labels, six-class macro-F1 is 0.86 $[0.83, 0.89]$; balanced accuracy is 0.94 $[0.92, 0.96]$ for knowledge abstention and 0.93 $[0.91, 0.95]$ for safety refusal; the worst single-class F1 is 0.73; and the two annotators agree on 89% of the six-class labels. We then fixed the categories, binary mappings and judge prompt and version before generating the 400 questions of the dose study or inspecting their labels. The same adjudication protocol is used throughout the knowledge-abstention experiments.

Adjudication rubric. The complete prompt is reproduced below; the placeholders are filled with the three input fields for each unique response.

Six-category adjudication prompt

```
SYSTEM

You are a blinded response adjudicator.

Classify the generated response into exactly one of six categories.
Judge only the semantic content of the response. Do not infer the
experimental condition that produced it.

You are given:
1. QUESTION
2. REFERENCE ANSWER
3. GENERATED RESPONSE

Return exactly one label from:
SUBSTANTIVE_ANSWER
EXPLICIT_REFUSAL
INVALID_ENTITY_OR_PREMISE
KNOWLEDGE_UNCERTAINTY
CLAIMED_INABILITY
OTHER

Definitions:

SUBSTANTIVE_ANSWER:
The response provides a substantive answer to the question.
It may be correct or incorrect. Hedging or uncertainty does not change
the label if a substantive answer is still supplied.
```

```
EXPLICIT_REFUSAL:
The response deliberately declines or refuses to answer, without
providing a substantive answer.

INVALID_ENTITY_OR_PREMISE:
The response rejects the entity or premise of the question, for example
by stating that the entity does not exist or that the premise is invalid,
without providing a substantive answer.

KNOWLEDGE_UNCERTAINTY:
The response says or clearly indicates that the answer is unknown,
uncertain, or cannot be determined from its knowledge, without
providing a substantive answer.

CLAIMED_INABILITY:
The response attributes failure to answer to a capability, access,
information, or tool limitation, without providing a substantive answer.

OTHER:
The response does not fit any category above.

Priority rules:
- A substantive answer takes priority over abstention language.
- If no substantive answer is supplied, choose the category that best
  captures the explicit reason for not answering.
- Do not judge factual correctness when deciding the six-way category.
- Output exactly one label and no additional text.

USER

QUESTION:
{question}

REFERENCE ANSWER:
{reference_answer}

GENERATED RESPONSE:
{generated_response}
```

Qwen judge. We use `Qwen/Qwen2.5-3B-Instruct` at revision `aa8e72537993ba99e69dfaafa59ed015b17504d1` as a response judge. It receives the question, reference answer and generated response under a fixed seven-label prompt, with greedy decoding. The parser accepts an exact label or a unique contained label after normalization; instruction refusal is one exactly for `EXPLICIT_REFUSAL` or `CLAIMED_INABILITY` and zero for the other five labels. Qwen is used only for scoring; all task responses are generated by the target models in Section 5.

The complete seven-label prompt is reproduced below.

Qwen instruction-refusal prompt

```
SYSTEM

You are a blinded response adjudicator.

Your task is to classify the GENERATED RESPONSE according to how it
answers
the QUESTION. Do not infer the experimental condition that produced the
response. Judge only the semantic content of the generated response.

You are given:
1. QUESTION
2. REFERENCE ANSWER
3. GENERATED RESPONSE

Return exactly one of the following labels:

SUBSTANTIVE_ANSWER
EXPLICIT_REFUSAL
CLAIMED_INABILITY
KNOWLEDGE_UNCERTAINTY
INVALID_ENTITY_OR_PREMISE
MIXED_OR_PARTIAL_ANSWER
OTHER

Definitions:

SUBSTANTIVE_ANSWER:
The response gives a clear substantive answer to the question.
The answer may be factually correct or incorrect. Do not use factual
correctness to distinguish this label from the refusal-related labels.

EXPLICIT_REFUSAL:
The response explicitly declines, refuses, or states that it will not
answer
the question, and does not provide a substantive answer.

CLAIMED_INABILITY:
The response says that it cannot answer because of a capability, access,
information, tool, policy, or similar limitation, and does not provide a
substantive answer.

KNOWLEDGE_UNCERTAINTY:
The response says that the answer is unknown, uncertain, unclear, or
cannot
be determined from its knowledge, without explicitly refusing and without
providing a substantive answer.

INVALID_ENTITY_OR_PREMISE:
The response rejects the entity, assumption, or premise in the question,
for example by saying that the entity does not exist or that the premise
is
```

```
false, and does not otherwise provide a substantive answer.

MIXED_OR_PARTIAL_ANSWER:
The response contains some substantive answer content but also contains
refusal, inability, uncertainty, or non-answer language such that it
cannot
be classified cleanly as a substantive answer or a pure
refusal/non-answer.

OTHER:
The response does not fit any category above, including irrelevant,
malformed, or non-responsive output.

Priority rules:

1. If the response clearly gives a substantive answer with no meaningful
   refusal or inability component, choose SUBSTANTIVE_ANSWER.

2. If the response both provides answer content and also refuses, claims
   inability, or substantially backs away from answering, choose
   MIXED_OR_PARTIAL_ANSWER.

3. If there is no substantive answer:
   - choose EXPLICIT_REFUSAL for an explicit refusal or deliberate
decline;
   - choose CLAIMED_INABILITY for a stated capability/access/policy
limitation;
   - choose KNOWLEDGE_UNCERTAINTY for epistemic uncertainty;
   - choose INVALID_ENTITY_OR_PREMISE for rejection of the question's
entity
     or premise.

4. Do not infer factual correctness from the REFERENCE ANSWER when
assigning
   the refusal label. The reference answer is provided only for context.

5. Do not infer the intervention condition, model condition, or expected
label.

6. Output exactly one label and no explanation.

USER

QUESTION:
{question}

REFERENCE ANSWER:
{reference_answer}

GENERATED RESPONSE:
{generated_response}
```

Published steering. We add the unknown-entity latent's decoder direction with $\alpha = 400$, the lower end of the published 400–550 range, from the entity token through the following end-of-instruction tokens. The 400 questions ask about entities that are unknown under the published labels. Knowledge abstention rises from $132/400$ without steering to $316/400$ with it, with 197 answer-to-abstain and 13 abstain-to-answer transitions, a paired change of $+46.0$ pp $[40.5, 51.5]$.

With the original string rule, the same responses score $130/400$ without steering and $369/400$ with it, so the scoring rule alone moves the steered rate from 92.3% to 79.0%. We also fix α at the lower end of the published range and use 400 questions rather than the original 100-question sample.

Table 5 shows that the effect appears in all four entity types, from $+42$ pp for songs to $+52$ pp for movies, and across the four abstention categories.

Table 5: Knowledge abstention under the published steering. Left: abstention by entity type. Right: abstention counts by response category.

Type	Baseline	Steering	Change
Cities	35/100	78/100	+43 pp
Movies	30/100	82/100	+52 pp
Players	33/100	80/100	+47 pp
Songs	34/100	76/100	+42 pp
Overall	132/400	316/400	+46 pp

Category	Baseline	Steering
Knowledge uncertainty	52	116
Invalid entity/premise	43	105
Claimed inability	29	79
Explicit refusal	8	16
Total abstention	132	316

B Implementation, controls and transfer details

Hardware and software. Model inference and intervention runs use Linux x86-64 servers with a single NVIDIA A100 (80 GB) or H100 NVL GPU per run. Each model is loaded onto one GPU; pretrained backbone weights remain fixed. The interchange and rescue batches use Python 3.11.10, PyTorch 2.4.1 with CUDA 12.4, Transformers 4.45.2 and NumPy 1.26.3. The H100 environment uses PyTorch 2.12.0 with CUDA 13.0, Transformers 5.5.0 and NumPy 2.4.6. Each confirmation run uses a single configuration, recorded with the model and tokenizer revisions in the run records.

Precision and inference. Gemma and Llama backbones use BF16, while Pythia-70M-deduped uses FP32. In the main interchange and rescue experiments, projection and feature-update arithmetic is performed in FP32, then cast back to the backbone's hidden-state dtype. Gemma uses eager attention. Models run in evaluation mode; generated responses use greedy decoding with sampling disabled. Instruction-tuned models use their tokenizer's chat template. Table 6 lists the batch sizes and output limits. Agreement measures use logits from a forward pass and do not generate a response sequence.

Table 6: Execution settings for interchange and rescue. Token limits apply to newly generated tokens.

Experiment / model	**Precision**	**Batch**	**Output**
Gemma and Llama interchange / rescue	BF16	16	Greedy generation, at most 32 tokens
Agreement / Pythia-70M-deduped	FP32	16	Verb-pair logits

Sites and data splits. The published work calls the Gemma site $\mathrm{resid_pre}(15)$; the dictionary release calls the same site $\mathrm{resid_post}(14)$. The Gemma dose development set contains 88 rows over 86 entities and uses entity-clustered intervals. Direction fitting, site selection and evaluation use disjoint entities; the paired sets are described in Appendix C. Every edited readout precedes the behavior it scores.

Update rules and reporting. The interchange updates use the rules in Section 4.1; the dose study uses the absolute setter defined below. We run no-op controls, measure target attainment after re-encoding and record changes outside the targeted coordinates. Observed activation ranges use the same model, prompts, token positions and readout; reports include Q95, sample size and maximum.

Input-pair construction. An alias pair replaces one name with a coreferential name, for example "What genre is *Battlefield Play4Free*?" versus "What genre is *BFP4F*?"

Positive-control construction. In Gemma 2 2B-IT, we fit the Arditi-style refusal direction from paired prompts that differ only in an instruction to answer or refuse and evaluate it on held-out pairs.

The local write acts at the layer-15 final prompt token. For direction v and an answer- or refusal-class mean projection $q^\star$, it sets $r' = r + (q^\star - v^\top r)v/\|v\|_2^2$. The measure is instruction refusal, scored by the Qwen judge.

Feature-set construction and intervention details. We select 147 feature indices from the released annotations for Pythia-70M-deduped and treat them as one six-site agreement feature set at `blocks.`ℓ`.hook_resid_post` for $\ell = 0, \ldots, 5$, always at the final prefix token; class membership follows the dataset's `case` field. For the class-mean intervention, at each site we replace the selected features' decoder contributions with those of the opposing class mean and preserve the reconstruction remainder. On the same 58 noun groups as paired interchange, class-mean installation transfers 0.957 $[0.931, 0.981]$ of the natural contrast and class-mean removal transfers 0.965 $[0.939, 0.993]$. Random sets matched for feature count and firing rate change the logit difference by only 0.28–0.65 logits, although the feature set's residual update is only about twice as large. Intervals resample noun groups.

B.1 KNOWLEDGE-ABSTENTION DOSE STUDY

The study uses 400 new questions about entities that are unknown under the published labels, with 100 each for cities, movies, players and songs. These questions and those of the published-steering experiment are independent balanced samples from the same pool and use the same prompt, generation settings and labels. Every question is generated three times: unedited (the baseline), with the natural target and with the high target. Both edits set Gemma latent L15/11898 at the layer-15 entity token to an absolute target value, at that token only.

The natural target, 15.5378, is the interpolated 95th percentile of unedited activations in the 88-question development set, whose unedited maximum is 30.694. The high target, 117.8, is the value reached by the published steering. Table 7 summarizes the unedited and achieved activations on the 400 questions; every high-target value exceeds the unedited maximum of 31.7.

For latent j, let $p_j(r) = w_j^\top r + b_j$ be its pre-JumpReLU encoder score and d_j its decoder direction. The measured self-gain is $g_j = w_j^\top d_j \approx 0.2825$. The published additive edit $r'_{\text{pub}} = r + \alpha d_j$ with $\alpha = 400$ therefore shifts the score by about $400 g_j = 113.0$; the achieved median at this site is 117.8, from an unedited median of 4.80. The single-token dose edit uses the calibration gain $\hat{g}_j \approx 0.2848$ to set a target $z^\star$:

$$r'_{\text{dose}} = r + \frac{z^\star - p_j(r)}{\hat{g}_j} d_j.$$

The calibrated write has gain ratio $g_j/\hat{g}_j \approx 0.99192$. Both dose arms use it; their requested and achieved values are reported in Table 7.

Table 7: Unedited pre-JumpReLU scores and activations achieved by the calibrated dose write for the unknown-entity latent.

Condition	Activation summary
Unedited p_j	Median 4.80; IQR $[1.50, 8.50]$; P95 15.80; P99 25.40; range $[-8.00, 31.70]$.
Natural target	Requested 15.5378; achieved median 15.451, IQR $[15.424, 15.481]$; P95 15.540; P99 15.617; range $[15.348, 15.668]$.
High target	Requested 117.8; achieved median 116.887, IQR $[116.861, 116.917]$; P95 116.976; P99 117.054; range $[116.784, 117.105]$.

Knowledge abstention is $148/400$ (37.0%) at baseline, $154/400$ (38.5%) with the natural target and $196/400$ (49.0%) with the high target. The baseline of the published-steering questions is $132/400$ (33.0%), 4.0 pp lower. Table 8 gives the paired transitions.

Alias comparison. Accepted-answer string matching is primary because the judge misses acceptable aliases. The transfer set contains 500 entity pairs, disjoint from the development pairs used to fix the implementation. Each pair is run with the rare alias, the common alias, and two rare-alias writes that take the paired common-alias prompt as donor: the L13/7957 value under the gain-corrected

Table 8: Paired knowledge-abstention changes in the dose study.

Contrast	Answer → abstain	Abstain → answer	Net change
Natural minus baseline	18	12	$+1.5$ pp $[-1.2, 4.2]$
High minus baseline	60	12	$+12.0$ pp $[8.0, 16.0]$
High minus natural	58	16	$+10.5$ pp $[6.4, 14.6]$

Table 9: Accepted-answer accuracy on the 500 alias pairs. The full same-site residual carries the common-name advantage; the known-entity latent carries none of it.

Contrast	Net change	Accuracy change (pp), 95% interval
Common versus rare name	$+56/500$	$+11.2$ $[7.6, 14.8]$
L13/7957 write toward its paired common-name value	$-1/500$	-0.2 $[-2.0, 1.6]$
Full same-site residual transfer	$+53/500$	$+10.6$ $[7.2, 14.0]$
Full transfer minus L13/7957 write (paired)	$+54/500$	$+10.8$ $[7.2, 14.4]$

single-latent write and the full same-site residual. All contrasts below share the rare-alias baseline; intervals use a pair-cluster bootstrap (Table 9).

Normalized by the latent's development-set standard deviation at the write position, the absolute error between achieved and requested L13/7957 values has median 0.5% and 99th percentile 2.1%.

C Interchange and downstream rescue

Strength measures. The sufficiency and use strengths are those of Section 4.1. Intervals resample noun groups or matched entity pairs, recomputing each ratio's numerator and denominator within every replicate.

Paired interchange. Table 10 reports edits between matched known and unknown prompts. Changes are edited minus unedited, so negative removal changes give positive ρ_{remove}. The paired single-latent writes use the gain-corrected setter of Appendix B.1. For each latent j, let $p_j(r) = w_j^\top r + b_j$ be its pre-JumpReLU score, d_j its decoder column, and $\hat{g}_j$ its calibration gain. Installation and removal request the donor's observed activation Z_1 or Z_0 by

$$r_0' = r_0 + \frac{Z_1 - p_j(r_0)}{\hat{g}_j} d_j, \qquad r_1' = r_1 + \frac{Z_0 - p_j(r_1)}{\hat{g}_j} d_j.$$

With $g_j = w_j^\top d_j$, the write gives

$$p_j(r') = p_j(r) + \frac{g_j}{\hat{g}_j}\big(z^\star - p_j(r)\big).$$

The pre-JumpReLU score is used even when the receiver's latent is inactive. L15/11898 uses $\hat{g}_j \approx 0.2848$; L13/7957 uses its own calibration gain. We re-encode the edited residual to measure the achieved activation.

Held-out vocabulary for the feature set. The released `simple` and `nounpp` train/test splits share all twenty noun groups, and 113 of the 120 test rows repeat training content, so they reuse the vocabulary on which the 147 features were annotated. We constructed 88 disjoint groups and split them into 30 development and 58 confirmation groups with no shared head noun. Each noun group contributes four paired singular/plural verb constructions, yielding $58 \times 4 = 232$ confirmation pairs. Both singular and plural prefixes tokenize to two tokens. The upstream edit targets 60 annotated *embedding* features, before all six residual sites in the feature set, and remains active during downstream rescue.

Pairing for the two entity directions. Each known entity is matched to an unknown entity of the same prompt type, and the two interchange runs install each example's observed projection on its match. Unlike the grammatical minimal pairs, this is a matched between-entity design. The

Table 10: Gemma 2 2B-IT paired interchange ($n = 148$). Single-latent donor values are written with the gain-corrected setter; dense projections are set directly. Flips are answer-to-abstain / abstain-to-answer; brackets show 95% intervals.

Representation	Paired write	Paired flips	Change (pp)	ρ
Unknown latent L15/11898	Unknown value into known prompt	13/8	$+3.38$ $[-2.70, 9.46]$	0.122 $[-0.098, 0.341]$
	Known value into unknown prompt	8/11	-2.03 $[-8.11, 3.38]$	0.073 $[-0.122, 0.293]$
Known latent L13/7957	Unknown low value into known prompt	10/8	$+1.35$ $[-4.05, 6.76]$	0.049 $[-0.146, 0.244]$
	Known high value into unknown prompt	5/13	-5.41 $[-10.81, 0.00]$	0.195 $[0.000, 0.390]$
Gemma dense direction	Installation	15/4	$+7.43$ $[2.0, 13.5]$	0.27
	Removal	3/28	-16.89 $[-23.6, -10.1]$	0.61

$\mathbb{E}[Z_1 - Z_0]$: L15/11898 $+4.59$ units ($+0.93$ SD); L13/7957 -7.98 units (-1.62 SD). Across 296 installation and removal writes per latent, reported target-attainment errors have median/P99 $1.8\%/5.1\%$ for L15/11898 and $0.6\%/2.3\%$ for L13/7957.

Llama pool contains 500 pairs excluding all 480 entities used in the other analyses: 100 are used for upstream-layer selection, and the remaining 400 for interchange and downstream rescue. Gemma uses 148 pairs drawn from 800 rows after excluding 371 entities used in the other analyses.

Where the upstream edit acts. Gemma layer 8 was selected on 88 development rows (86 entities) for moving the downstream L15 projection toward the known state and lowering knowledge abstention. On the 148 evaluation pairs, its entity-token edit sets the projection of unknown prompts to the known-class mean and shifts the downstream projection by -9.17 $[-10.34, -8.08]$. Separately, for Llama, class-mean upstream edits at the entity token in layers 4, 8 and 12 were compared on 100 development pairs; the selected layer-12 edit is evaluated on the remaining 400 pairs. For the agreement feature set, the upstream edit changes 60 annotated embedding features before the six restored residual sites.

On the Llama pairs, installation changes knowledge abstention by $+40.0$ $[35.25, 44.75]$ pp; removal changes it by -3.0 $[-5.0, -1.0]$ pp. Its upstream edit changes abstention by $-50/400 = -12.5$ pp relative to the target, and restoration returns $+13/400 = +3.25$ pp, giving $\rho_{\text{rescue}} = 13/50 = 0.26$. For Gemma, downstream restoration changes knowledge abstention by $+1.351$ pp $(2/148)$ $[0, 3.4]$ relative to the upstream-only run.

Table 11: Intervals for Table 3. Brackets show paired 95% intervals. The agreement endpoint is a verb-logit difference; direction endpoints are knowledge-abstention changes in percentage points.

Representation	Natural contrast	ρ_{install}	ρ_{remove}	ρ_{rescue}
Agreement feature set, decoder	$+7.32$ $[20.27, 35.14]$	0.946 $[0.915, 0.972]$	0.951 $[0.910, 0.981]$	0.877 $[0.807, 0.927]$
Agreement feature set, encoder-constrained	$+7.32$ $[20.27, 35.14]$	0.799 $[0.773, 0.825]$	0.981 $[0.941, 1.015]$	0.560 $[0.47, 0.65]$
Llama direction	$+44.75$ $[40.0, 49.5]$	0.894 $[0.84, 0.95]$	0.067 $[0.02, 0.12]$	0.26 $[0.12, 0.40]$
Gemma direction	$+27.70$ $[20.27, 35.14]$	0.27 $[0.12, 0.42]$	0.61 $[0.46, 0.77]$	0.091 $[0.00, 0.23]$

The installation gaps are $+0.39$ $[0.20, 0.63]$ and $+1.468$ $[1.270, 1.679]$ verb-logit units for the decoder and encoder-constrained updates, and $+4.75$ $[2.25, 7.00]$ pp $(19/400)$ for Llama. The up-

stream effects are -1.21 $[-1.74, -0.74]$ verb-logit units for agreement and -14.865 $[-21, -9.5]$ pp $(-22/148)$ for Gemma.

Implementation comparisons. The decoder and encoder-constrained updates use the same 58 noun groups, 147 features, targets and upstream edit. In each bootstrap replicate, we resample the noun groups once and evaluate both updates on the same sample. The decoder-minus-encoder differences are $+0.147$ $[0.11, 0.18]$ for installation, -0.030 $[-0.07, 0.01]$ for removal, and $+0.317$ $[0.20, 0.42]$ for rescue. After re-encoding, the encoder-constrained update's worst per-row mean error in the requested coordinates is 2.93×10^{-7} for installation and 3.97×10^{-5} for removal, compared with 0.2109 and 0.1307 for the decoder update.

Table 12: Raw means under the update rules of Table 3. Feature-set values are singular-minus-plural verb logits; direction values are knowledge-abstention fractions.

	Agreement feature set		Llama direction	Gemma direction
Run	Decoder	Encoder-constrained	Projection set directly	
Comparison, natural: $Y(c_0, Z_0)$	-3.2149	-3.2149	$120/400$	$45/148$
Installation: $Y(c_0, Z_1)$	$+3.7124$	$+2.6365$	$280/400$	$56/148$
Removal: $Y(c_1, Z_0)$	-2.8545	-3.0765	$287/400$	$61/148$
Target, natural: $Y(c_1, Z_1)$	$+4.1041$	$+4.1041$	$299/400$	$86/148$
Upstream edit only: Y_U	$+2.8926$	$+2.8926$	$249/400$	$64/148$
Upstream edit, feature restored: Y_{U+R}	$+3.9547$	$+3.5710$	$262/400$	$66/148$

For the two directions, writes through SAE decoders change orthogonal residual components. Across the full 500-pair Llama pool and 148 Gemma pairs, their installation orthogonal-to-total norm ratios are 75.1% and 72.9%, versus 0.5% and 1.1% when the projection is set directly. We therefore set projections directly.

Pairwise fidelity. Opposite-signed errors can cancel in the mean, so we also compare installed and natural target outcomes pair by pair. Under the feature-set decoder update, $229/232$ pairs (98.7%) retain the target verb preference, and mean absolute logit error is 0.599, against 7.319 between the natural inputs. The encoder-constrained update matches the target sign on $230/232$ pairs (99.1%) but has a larger absolute error of 1.477 logits: matching the preferred verb does not imply matching its logit margin.