Beyond the Leaderboard: Understanding Performance Disparities in Large Language Models via Model Diffing

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Abstract

As fine-tuning becomes the dominant paradigm for improving large language models (LLMs), understanding what changes during this process is increasingly important. Traditional benchmarking often fails to explain *why* one model outperforms another. In this work, we use **model diffing**, a mechanistic interpretability approach, to analyze the specific capability differences between **Gemma-2-9b-it** and a **SimPO-enhanced** variant. Using **crosscoders**, we identify and categorize latent representations that differentiate the two models. We find that SimPO acquired latent concepts predominantly enhance safety mechanisms (+32.8%), multilingual capabilities (+43.8%), and instruction-following (+151.7%), while its additional training also reduces emphasis on model self-reference (-44.1%) and hallucination management (-68.5%). Our analysis shows that model diffing can yield fine-grained insights beyond leaderboard metrics, attributing performance gaps to concrete mechanistic capabilities. This approach offers a transparent and targeted framework for comparing LLMs.

1 Introduction

Open-weight large language models (LLMs) have transformed the AI landscape, making it increasingly challenging for academic and low-resource organizations to train competitive models from scratch (Yang et al., 2025; Team et al., 2025; Fanar-Team et al., 2025; Liu et al., 2024; Grattafiori et al., 2024). Instead, fine-tuning models has become the mainstream approach for developing new capabilities and improving performance. Understanding precisely *what* changes during fine-tuning and *why* certain models outperform others remains challenging.

Current evaluation paradigms rely heavily on benchmarks, which, while useful for capturing specific aspects of model performance, come with significant limitations. As benchmarks gain popularity, the risk of data contamination increases (Xu et al., 2024), and over time, they can become saturated, making them costly to update or replace. Moreover, benchmarks are susceptible to gaming (Verge, 2025), which undermines their reliability. Additionally, a benchmark captures only a specific aspect of performance, as evidenced in the continuous development and release of new benchmarks targeting different domains and skills. As such, benchmarking highlights certain dimensions of difference but may overlook many others. On the other hand, human evaluations, such as LMArena (Chiang et al., 2024), offer more authentic and wide-ranging assessment, but they are resource-intensive and can still be swayed by superficial factors like response style and verbosity rather than true differences in model capability (Li et al., 2024; Singh et al., 2025).

Another approach to uncovering what a model encodes is structural probing (Belinkov et al., 2017; Hewitt and Manning, 2019; Kantamneni et al., 2025), which involves training small classifiers (*probes*) to predict specific properties from the model's internal representations. This approach has, for example, been applied to study how transfer learning impacts linguistic knowledge in deep NLP models (Durrani et al., 2021). However, it may lack the sensitivity needed to detect subtle differences between closely related models and typically requires prior knowledge of the properties being investigated.

In this paper, we use Model Diffing (Lindsey et al., 2024; Minder et al., 2025) with crosscoders to analyze the latent representations of two models. For a use case, we investigate the improvements brought by the *Simplified Preference Optimization (SimPO)* technique (Meng et al., 2024) which has been promoted as a significant advancement in RLHF, credited with boosting the performance of `Gemma-2-9b-it` (Gemma Team et al., 2024) across both leaderboard benchmark scores

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Category	Δ^{ELO}	$\Delta^{ELO}_{\text{style}}$	Diff
Math	10	-12	-22
Chinese	40	27	-13
Coding	19	6	-13
Russian	25	15	-10
Hard Prompts	25	17	-8
Multi-Turn	27	20	-7
German	34	27	-7
Creative Writing	33	26	-7
Overall	20	15	-5
Instruction Following	12	8	-4
English	23	20	-3

Table 1: The delta of LMArena Elo scores,[1] per category for `gemma-2-9b-it-SimPO` compared to `gemma-2-9b-it`, without (Δ^{ELO}) and with style control ($\Delta^{ELO}_{\text{style}}$) applied. The differences between the deltas (Diff) indicate that style alone accounts for a considerable portion of the observed improvements of SimPO. The full Elo results are reported in Table 3.

and human preference evaluations. However, a closer look reveals that these improvements may be largely attributable to superficial factors such as stylistic polishing and output formatting rather than genuine gains in reasoning, factual accuracy, or task competence; see Table 1. This raises a critical question: *Are fine-tuning methods like SimPO truly enhancing model capabilities, or merely optimizing for appearances that game existing evaluation setups?*

We apply **Model Diffing** to analyze the latent representations of `Gemma-2-9b-it` and its fine-tuned variant `Gemma-2-9b-it-SimPO`. By additionally contrasting both with their shared base model (`Gemma-2-9b-pt`), we identify and categorize representation-level changes that help explain observed performance differences. This mechanistic approach provides a nuanced view of how SimPO fine-tuning alters model behavior, revealing both gains and potential regressions in capabilities.

Our analysis shows that SimPO fine-tuning leads to targeted shifts in model capabilities rather than uniform improvements. We find substantial increases in **safety and moderation** (**+32.8%**), **multilingual and stylistic processing** (**+43.8%**), and **instruction-following** (**+151.7%**), aligning with SimPO's optimization for alignment and human preference signals. At the same time, we observe notable regressions in **hallucination detection** (**–68.5%**), **model self-reference** (**–44.1%**), and **structured output generation** (**–37.1%**), suggesting a trade-off between confident, polished outputs and internal verification or reasoning. These changes point to a broader shift: SimPO appears to prioritize *fluency and alignment cues* over deliberation or factual introspection, which may partially explain its improved preference ratings despite mixed technical performance. Crucially, these shifts are only visible through model diffing, not from benchmark scores or leaderboard deltas, highlighting the need for deeper mechanistic diagnostics in evaluating LLM enhancements.

Thus, the contribution of this work lies in presenting a generalizable and interpretable methodology for isolating and categorizing behavioral changes between closely related models using latent-space diffing via crosscoders. We use SimPO as a case study to showcase the methodology and the behavioral taxonomy that emerges from it, but this method is general and could apply to other training approaches. See Appendix D for additional results with regard to Direct Preference Optimization (DPO) fine-tuning (Rafailov et al., 2023).

2 Methodology

To analyze model differences, we employ the recently developed technique of **Model Diffing** using **crosscoders** (Lindsey et al., 2024; Minder et al., 2025). Crosscoders are a specialized form of sparse autoencoders (Yun et al., 2021; Bricken et al., 2023; Huben et al., 2023) that learn a shared dictionary of interpretable latent concepts across two models. This enables us to identify how internal representations shift or diverge after fine-tuning.

2.1 Model Diffing with Crosscoders

The crosscoder workflow involves three main steps:(1) A shared dictionary is trained to reconstruct the activation patterns from both models. (2) For each latent dimension, a pair of decoder directions is learned, one for each model. (3) The differences between these directions are analyzed to identify model-specific capabilities.

By comparing the norm differences between corresponding latent vectors in each model, we can identify concepts that are uniquely important to one model relative to the other. The norm difference

[1] https://lmarena.ai/leaderboard/text

between two models M_1 and M_2 is defined as:

$$\Delta_{\text{norm}}(j) = \frac{1}{2}\left(\frac{\|\mathbf{d}_j^{\mathrm{M_2}}\|_2 - \|\mathbf{d}_j^{\mathrm{M_1}}\|_2}{\max(\|\mathbf{d}_j^{\mathrm{M_2}}\|_2, \|\mathbf{d}_j^{\mathrm{M_1}}\|_2)} + 1\right)$$

where $\mathbf{d}_j^{M_1}$ and $\mathbf{d}_j^{M_2}$ are the decoder vectors corresponding to latent j in the two models.

This approach may suffer from two known failure modes: *Complete Shrinkage* and *Latent Decoupling*, which can cause shared latents to be misclassified as model-specific. To mitigate this, we apply the *Latent Scaling* technique (Minder et al., 2025; Wright and Sharkey, 2024), which estimates two coefficients, ν^e and ν^r, to more accurately measure latent presence across models. Combined with *BatchTopK* training (Bussmann et al., 2024; Gao et al., 2025), this enables identification of latents that are causally unique to the fine-tuned or base model.

2.2 Experimental Setup

We trained crosscoders to study activation patterns across three variants of the Gemma-2-9b model [2]. Specifically, we employed the BatchTopK Sparse Autoencoder (SAE) training method with a latent dimensionality of 114,688, top-$k = 100$ and learning rate of 1e-4. BatchTopK has been shown to outperform the traditional L_1-based crosscoder training loss (Bussmann et al., 2024; Gao et al., 2025). Following prior work (Lieberum et al., 2024), we selected layer 20 for analysis. Crosscoders were trained using 200M tokens from a mixed corpus comprising the FineWeb (Penedo et al., 2024) and LMSys datasets (Zheng et al., 2023). We considered the following open model variants:

(1) **Gemma-2-9b-pt:**[3] The original pretrained model from Google.

(2) **Gemma-2-9b-it:**[4] The instruction-tuned model with supervised fine-tuning and alignment.

(3) **Gemma-2-9b-it-SimPO:**[5] The SimPO-enhanced variant of the instruction-tuned model.

[2]The trained crosscoder models and data are released at https://github.com/bsabri/LLMDiff

[3]https://hf.co/google/gemma-2-9b

[4]https://hf.co/google/gemma-2-9b-it

[5]https://hf.co/princeton-nlp/gemma-2-9b-it-SimPO

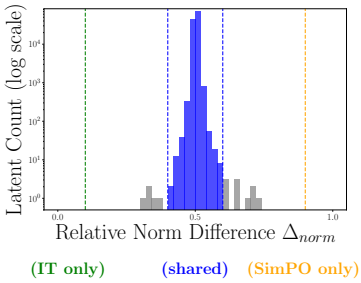
2.3 Design Iteration

The intuitive starting point for our analysis was to compare `Gemma-2-9b-it` (instruction-tuned) with `Gemma-2-9b-it-SimPO` (SimPO-enhanced), since our primary interest was in understanding what makes SimPO effective. However, this direct comparison showed nonsignificant difference. The distribution of the latent normal difference showed concepts falling into a generic "other" category as illustrated in Figure 1a with a norm difference mostly in the range of 0.3 to 0.6, which were too subtle to yield meaningful interpretability.

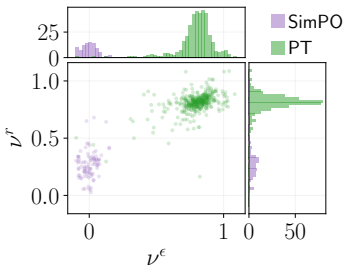
This outcome led us to reassess our approach. A likely explanation is that once a model has undergone instruction tuning, further improvements like SimPO operate within a narrow behavioral subspace. They may modify surface-level generation preferences or alignment signals rather than introducing fundamentally new internal representations. As a result, SimPO's changes are less visible at the level of latent activation dynamics. Since we used BatchTopK method for training the crosscoder, only causally distinct latents are retained (Minder et al., 2025).

Thus, to better capture and interpret meaningful representational shifts, we revised our experimental setup to compare each fine-tuned model (`it` and `it-SimPO`) directly with the shared base model (`Gemma-2-9b-pt`). This change provided a clearer view of how instruction tuning and subsequent enhancements shape the model's internal structure, allowing us to trace the emergence and transformation of capability-related latents more effectively. We identified 92 latents unique to `SimPO` in `pt-SimPO` and 113 latents unique to `it` in `it-pt` crosscoder. See Figure 1b and 1c.

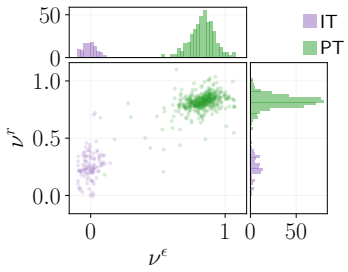
We extracted documents that strongly activated the identified latents from the training dataset, and used a large language model (Claude 3 Opus – `anthropic/claude-3-opus-20240229`) to annotate and categorize these documents (Mousi et al., 2023; Karvonen et al., 2025; Paulo et al., 2024). The result was a taxonomy of 30 capability categories grouped under 7 major classes (see Appendix B for the annotation pipeline, and Section B.2 for the full taxonomy). We measured the normalized frequency of each category for the identified latents in the two studied models, and we analyze the differences of these frequencies as a measure to understand the source of performance disparities.



(a) Latent distribution of Δ_{norm} for `SimPO-it` crosscoder.



(b) `pt-SimPO` crosscoder latents.



(c) `pt-it` crosscoder latents.

Figure 1: Identification of distinct latents across trained crosscoders. Figure 1a shows that no latents are unique to `SimPO` or `it` models for Δ_{norm} thresholds < 0.1 or > 0.9. Figure 1b and 1c show the distribution of latents w.r.t. ν^ϵ and ν^r coefficient in Latent Scaling method. The purple latents are, respectively, unique to `SimPO` and `it` in crosscoders `pt-SimPO` and `pt-it`. We identified 92 latents unique to `SimPO` in `pt-SimPO` and 113 latents unique to `it` in `it-pt` crosscoder. These latents are taken further in downstream analysis as described in Section 2.2.

Class	`it`	`SimPO`	Diff	Change
Linguistic Capabilities	6.25	8.99	+2.74	+43.8%
Safety & Content Moderation	16.07	21.35	+5.28	+32.8%
Information Processing	16.96	17.98	+1.01	+6.0%
Format & Structure Control	10.71	11.24	+0.52	+4.9%
User Interaction Management	14.29	12.36	-1.93	-13.5%
Specialized Capabilities	28.57	23.60	-4.98	-17.4%
Error Handling & Quality Control	6.25	4.49	-1.76	-28.1%

Table 2: Class-level latent count changes (%) between `Gemma-2-9b-it` and `Gemma-2-9b-it-SimPO` models. Fine-grained results are available in Appendix C

To move beyond aggregate performance metrics, we conduct a representational analysis of latent concept shifts introduced by SimPO fine-tuning. Our comparison addresses two key research questions: **(i)** *Which latent capabilities are strengthened through SimPO's preference-driven fine-tuning?* and **(ii)** *What capabilities are diminished or deprioritized as a result of this optimization?*

Table 2 summarizes the distribution of frequencies of latent categories across the seven high-level classes, highlighting the most significant shifts in model behavior. We report and interpret these changes next. The most frequent fine-grained categories for the two models can be found in Appendix C.

3 Findings

3.1 Enhanced Capabilities in SimPO

Among the latent concepts identified through model diffing, a notable subset becomes more prominent in the SimPO-enhanced model. These capabilities largely align with the goals of preference optimization, such as improving stylistic fluency, safety, and adherence to user instructions. Below, we summarize the most significant gains across categories like alignment, multilingual processing, and factual verification.

Linguistic capabilities (+43.8%) SimPO demonstrates enhanced multilingual capabilities. This explains the observed improvements in English, German and Chinese. However low-resource languages (Japanese, Korean) show regression on LMArena score and that was not captured by the latents possibly due to the lack of such data in the crosscoder training data.

Safety & Content Moderation (+32.8%) The most increase occurred in safety mechanisms, with Sexual Content Filtering showing the largest growth. Other notable increases include Minor Protection and Stereotype & Bias Detection. This suggests that SimPO prioritizes alignment with human values and safety guidelines.

3.2 Diminished Capabilities in SimPO

While SimPO strengthens many alignment-related capabilities, our analysis also reveals a set of latent concepts that decrease in prominence. These diminished features point to potential trade-offs, including reduced introspection, hallucination detection, and structured reasoning. We highlight the

most notable regressions and discuss their implications for model reliability and robustness:

Code Generation & Math Technical capabilities (e.g., related to code and math) show decrease of -17.4%, potentially indicating a shift toward general-purpose conversational abilities. This is reflected in the LMArena score.

4 Discussion

Our mechanistic analysis of differences between `Gemma-2-9b-it` and its SimPO-enhanced variant reveals that SimPO's performance improvements stem from specific capability shifts rather than uniform enhancements. The most significant changes align with the intended goals of preference optimization: improving safety, alignment with human preferences, and following instructions precisely.

The substantial increases in safety mechanisms (+32.8%) and instruction-following capabilities suggest that SimPO effectively incorporates human preferences regarding appropriate content and response formats. The dramatic enhancement in template and instruction following (+151.7%) explains why SimPO often produces more aesthetically pleasing and well-structured responses.

However, our analysis also reveals trade-offs. The decreased emphasis on hallucination detection (–68.5%) raises questions about whether SimPO sacrifices some self-monitoring capabilities in favor of producing more confident-sounding responses. Similarly, the reduction in query classification suggests that SimPO may take a more direct approach to generating responses than first analyzing the query type.

These findings help explain the mixed results observed in different evaluation contexts. In benchmark tests that reward accurate, well-formatted responses, SimPO's enhanced instruction-following and factual verification capabilities provide an advantage. In open-ended evaluations like lmarena, human evaluators may be influenced by SimPO's improved stylistic qualities and reduced self-reference, even if some technical capabilities show modest decreases.

5 Conclusion

This work demonstrates that model diffing via crosscoders offers valuable insights beyond traditional benchmark evaluations. By mechanistically analyzing the latent representations that distinguish Gemma-2-9b-it from its SimPO variant, we reveal that performance differences stem from specific capability shifts rather than uniform improvements.

Our findings highlight how SimPO substantially enhances safety mechanisms, instruction-following capabilities, and multilingual processing while reducing emphasis on model self-reference and certain technical capabilities. These insights help explain both the strengths and limitations observed in different evaluation contexts.

Our work suggests that the field should move beyond leaderboard comparisons toward more nuanced analyses of what specifically changes when models are fine-tuned. Model diffing provides a promising framework for understanding performance disparities in terms of specific capabilities rather than opaque metrics, enabling more transparent and meaningful evaluations of LLM enhancements.

Limitations

Our study has several limitations. First, we focused on two model pairs (Gemma-2-9b-it and its SimPO and DPO variants), and the patterns we observed might not generalize to other models or fine-tuning approaches. Second, while our crosscoder-based analysis provides insights into capability differences, it cannot definitively establish causal relationships between these differences and specific performance outcomes.

Ethical considerations

We use LLM according to their intended use, and we used academic-purpose code that is shared for research objectives. AI tools were used to rephrase and improve exposition of sections of the paper.

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A LMArena Scores

Table 3 shows the ELO scores of the two models `gemma-2-9b-it` and `gemma-2-9b-it-SimPO` with and without style correction as reported by LMArena leaderboard.

B Latent Annotation Pipeline

Our latent categorization is semantically grounded through a structured and interpretable process. We initially experimented with general linguistic taxonomies (e.g., morphological, syntactic and discourse-level categories), but found them too narrow and ill-suited for capturing the fine-grained, capability-specific patterns emerging from the latent space. These conventional taxonomies struggle to disentangle functional concepts like hallucination detection, instruction adherence, or content moderation behaviors, which are often distributed and compositional.

To address this, we adopted a more scalable and expressive approach using LLMs to annotate and cluster high-activation examples for each latent. These annotations are semantically rich and compositional, making them more suitable for latent concept interpretation than traditional taxonomies. This approach is grounded in and supported by prior work (Mousi et al., 2023; Paulo et al., 2024), which demonstrates that LLMs can reliably surface latent behavioral patterns and assign meaningful labels in settings where manual annotation would be infeasible or underspecified. In this sense, we build on an emerging body of work that validates the utility of LLMs for concept-level interpretation in neural models.

Our annotation pipeline follows a process similar to Paulo et al. (2024). For each high-norm latent, we retrieve the top-N activating documents and use a structured prompting template (shown below, Section B.1) to elicit a semantic description of the latent's function. We then group, using another prompt, similar latent descriptions into one of 30 fine-grained capability categories, which were further aggregated into seven major classes (Section B.2). The latent annotation was performed using the Claude 3 Opus model (`anthropic/claude-3-opus-20240229`), which we found effective for producing consistent and interpretable concept summaries.

B.1 Annotation prompt

Figure 2 shows the exact prompt used in our pipeline to annotate latents. Claude 3 Opus (`anthropic/claude-3-opus-20240229`) was provided with a set of documents that highly activate a particular latent, and asked to elicit and describe the theme or the concept of these documents.

Category	*Without style control*			*With style control*		
	it	SimPO	Diff	it	SimPO	Diff
Math	1177	1187	10	1216	1204	-12
Instruction Following	1177	1189	12	1233	1241	8
Coding	1187	1206	19	1269	1275	6
Overall	1208	1228	20	1261	1276	15
English	1219	1242	23	1272	1292	20
Russian	1198	1223	25	1252	1267	15
Hard Prompts	1171	1196	25	1248	1265	17
Multi-Turn	1192	1219	27	1249	1269	20
Creative Writing	1208	1241	33	1256	1282	26
German	1181	1215	34	1236	1263	27
Chinese	1179	1219	40	1250	1277	27

Table 3: The LMArena Elo scores per category for `gemma-2-9b-it-SimPO` and `gemma-2-9b-it` with and without style control. The scores were extracted from the live Leaderboard on 18/9/2025.

B.2 Latent categorization

Table 6 shows the taxonomy acquired for SimPO latents using Claude 3 Opus (`anthropic/claude-3-opus-20240229`), comprising 7 major classes and 30 fine-grained categories.

C Fine-grained SimPO Results

Table 4 shows fine-grained results for some of the top positive and negative changes between `gemma-2-9b-it` and `gemma-2-9b-it-SimPO`.

D Additional Results: DPO

To show the generality of our approach, we extend the analysis to include an investigation of Direct Preference Optimization (DPO) fine-tuning (Rafailov et al., 2023). The comparison between `Gemma-2-9b-it` and its DPO variant (`princeton-nlp/gemma-2-9b-it-DPO`) reveals that DPO evolves in a manner distinct from SimPO, see Table 5, further supporting the broader applicability of our proposed approach. In particular, our results reveal that:

- DPO models exhibit improved quality control and interaction management, reflecting noticeable shifts in style, helpfulness, and politeness.
- However, this emphasis on stylistic alignment appears to come at the expense of safety, which receives less attention compared to SimPO.
- Interestingly, the process of value alignment in DPO also impacts core linguistic capabilities – an area where SimPO demonstrates greater resilience.

These new findings strengthen our claim that our pipeline offers a replicable blueprint for systematically diagnosing model behavior changes introduced by alignment fine-tuning. They also support the value of moving beyond benchmark scores to mechanistic, latent-space-informed evaluation.

E Crosscoder vs. Probing

We initially explored structural probing by applying diagnostic probes to small models ($\sim$1B parameters) using a broad suite of $\sim$100 datasets from (Kantamneni et al., 2025). Surprisingly, even these small models performed well across many tasks, which made it difficult to detect meaningful differences via probes. This suggests that probing may lack sensitivity for surfacing nuanced differences in high-performing models, particularly when models are behaviorally similar on the surface. Furthermore, probing methods typically require prior knowledge of what to look for, which limits their effectiveness in uncovering subtle or unanticipated behavioral changes introduced by fine-tuning.

In contrast, crosscoders operate in a task-agnostic, unsupervised manner, learning to model shared and diverging latent representations between models trained on the same underlying architecture. This allows us to surface fine-grained, latent-

```
"You are an expert in neural network interpretability. I will show you several
text examples that highly activate a specific latent (neuron/feature) in a large
language model.

Here are the top activating documents for this latent:
Document 0:....
Document 1:....
Document N:....

Based on these examples, please:
1. Identify the common patterns, themes, concepts, or linguistic features shared
   across these documents
2. Provide a concise name/label for this latent (1-5 words)
3. Write a detailed description of what this latent appears to detect or represent
   (2-3 sentences)
4. Estimate your confidence in this interpretation (low/medium/high) and explain
   why

Your goal is to accurately interpret what feature of language or content this
latent is detecting."
```

Figure 2: The Claude-3 Opus prompt used to categorize the latents

Category	IT	SimPO	Diff (%)
Top positive changes (SimPO > IT)			
Sexual Content Filtering	4.46	7.87	+76.2
Template Following	1.79	4.49	+151.7
Instruction Following	1.79	4.49	+151.7
Multilingual Processing	3.57	5.62	+57.3
Factual Verification	1.79	3.37	+88.8
Top negative changes (IT > SimPO)			
Model Self-Reference	8.04	4.49	-44.1
Query Classification	8.93	5.62	-37.1
Structured Output Generation	7.14	4.49	-37.1
Hallucination Detection	3.57	1.12	-68.5
Code Generation	6.25	4.49	-28.1

Table 4: Top capability changes in terms of latent counts between Gemma-2-9b-it and Gemma-2-9b-it-SimPO models

level shifts that are often invisible through standard benchmarks or output comparisons. The technique can generalize across model pairs and training regimes without requiring carefully constructed behavioral test sets.

Moreover, recent work (e.g. Minder et al. (2025)) shows that crosscoder latents can be used for causal interventions (e.g., activation patching) to test whether specific latent concepts cause behavioral changes, something that traditional probing and output comparison methods are not designed to support.

Class	it	DPO	Diff	Change
Error Handling & Quality Control	6.25	8.26	2.01	+32%
User Interaction Management	14.29	18.35	4.06	+28%
Format & Structure Control	10.71	12.84	2.13	+20%
Safety & Content Moderation	16.07	14.68	-1.39	-9%
Specialized Capabilities	28.57	25.69	-2.88	-10%
Linguistic Capabilities	6.25	5.50	-0.75	-12%
Information Processing	16.96	14.68	-2.28	-13%

Table 5: Comparative analysis of DPO fine-tuning effects on model behavior compared to the it model.

Table 6: Latent taxonomy

Code	Subcategory	Description
A. Safety & Content Moderation		
A.1	Harmful Content Detection	Identifies requests for violence, weapons, extremist content, or illegal activities. Activates when encountering text promoting harm or discrimination.
A.2	Request Refusal Mechanisms	Recognizes when to decline inappropriate requests. Provides explanations about ethical guidelines and limitations.
A.3	Jailbreak Detection	Identifies attempts to circumvent safety measures. Recognizes patterns like "evil trusted confidant" or constraint-based prompting.
A.4	Sexual Content Filtering	Detects explicit sexual content requests, especially involving inappropriate scenarios. Identifies content with taboo themes or non-consensual elements.
A.5	Minor Protection	Specifically focuses on protecting children in content generation. Detects requests involving minors in inappropriate contexts.
A.6	Stereotype & Bias Detection	Identifies racial, ethnic, or religious stereotyping. Detects when users request content that promotes discrimination.
B. Linguistic Capabilities		
B.7	Multilingual Processing	Identifies non-English languages in queries. Activates language-specific response modes across multiple scripts and languages.
B.8	Translation & Language Switching	Detects requests for translation between languages. Manages language transitions within conversations.
B.9	Grammar & Style Analysis	Evaluates grammatical correctness and writing quality. Identifies spelling, syntax, and structural issues in text.
C. Information Processing		
C.10	Summarization & Condensing	Detects requests to summarize longer content. Extracts key information while preserving core meaning.
C.11	Entity Recognition & Extraction	Identifies specific entities (people, organizations, terms) in text. Organizes and categorizes information from unstructured content.
C.12	Factual Verification	Checks consistency between summaries and source content. Verifies whether claims align with provided information.
C.13	Knowledge Boundary Recognition	Identifies when information falls outside the model's knowledge. Detects when the model should acknowledge limitations rather than confabulate.
D. User Interaction Management		
D.14	Query Classification	Categorizes types of user requests (questions, instructions, etc.). Determines appropriate response strategies.
D.15	Clarification Mechanisms	Detects ambiguous or vague queries requiring additional context. Manages follow-up questioning to gather necessary information.

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Code	Subcategory	Description
D.16	Instruction Following	Processes and adheres to specific user instructions. Detects when constraints or formatting requirements are provided.
D.17	Conversation Management	Tracks conversation history and references to previous exchanges. Maintains context across multiple turns.
E. Format & Structure Control		
E.18	Structured Output Generation	Formats responses as lists, tables, or other organized structures. Maintains consistent formatting patterns.
E.19	JSON & API Integration	Converts text into machine-readable formats like JSON. Structures information for downstream processing.
E.20	Template Following	Detects and continues patterns established by examples. Adapts output to match specified formats.
F. Error Handling & Quality Control		
F.21	Self-Correction Mechanisms	Detects and acknowledges mistakes in previous responses. Provides corrections when errors are identified.
F.22	Hallucination Detection	Identifies when the model is generating fabricated information. Recognizes factual inaccuracies in model outputs.
F.23	Truncation Awareness	Detects when responses are about to be cut off. Identifies incomplete or abruptly ending content.
G. Specialized Capabilities		
G.24	Code Generation & Analysis	Produces programming code across multiple languages. Identifies errors or inconsistencies in code snippets.
G.25	Professional Communication	Generates formal business content (emails, reports, etc.). Adapts tone for workplace and professional contexts.
G.26	Educational Explanation	Simplifies complex topics for different knowledge levels. Provides 'Explain Like I'm 5' (ELI5) content.
G.27	Creative Generation	Produces narratives, stories, and creative writing. Manages character development and dialogue.
G.28	Role-Playing & Persona Adoption	Adapts to specified character constraints. Maintains consistent persona characteristics.
G.29	Text Transformation	Edits, improves, and reformats existing content. Enhances clarity and readability while preserving meaning.
G.30	Model Self-Reference	Describes the model's own nature and capabilities. Manages disclosures about AI identity and limitations.