Hierarchical Alignment: Surgical Fine-Tuning via Functional Layer Specialization in Large Language Models

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Abstract

While standard Direct Preference Optimization (DPO) treats Large Language Models as monolithic blocks, we propose Hierarchical Alignment, a surgical fine-tuning framework that leverages the functional specialization inherent in Transformer architectures by selectively optimizing distinct layer blocks: shallow (Local-Align), middle (Mid-Align), and deep (Global-Align). Through extensive evaluation across four state-of-the-art model families (Llama-2/3.1 and Qwen-2.5/3) using a rigorous 16-dimensional "LLM-as-Judge" protocol, we demonstrate that Mid-Align consistently matches or exceeds the performance of full-parameter DPO despite a significant reduction in updated parameters, identifying the middle layers as the critical nexus for semantic coherence and knowledge integration. Our findings reveal a fundamental "bottom-up" representational dependency—where late-layer updates alone prove insufficient for behavioral alignment—and establish that hierarchical strategies induce predictable, dimension-specific shifts in model behavior, ultimately advocating for a transition toward architecture-aware alignment as a more efficient, interpretable, and controllable paradigm for shaping intelligent systems.

1 Introduction

The alignment of Large Language Models (LLMs) with human preferences has transitioned from complex reinforcement learning pipelines to more stable, direct optimization objectives, most notably Direct Preference Optimization (DPO) (Rafailov et al., 2024). Despite this algorithmic progress, a fundamental "black-box" assumption persists: current alignment paradigms treat LLMs as monolithic entities, applying uniform parameter updates across the entire network depth. This one-size-fits-all approach ignores a decade of interpretability research suggesting that Transformers are functionally specialized (van Aken et al., 2019). While lower layers typically govern local syntax and linguistic tokens, middle and upper layers specialize in semantic coherence and global intent integration. Aligning a model by brute-force updates across all layers is akin to a master surgeon using a sledgehammer—a lack of precision that may lead to catastrophic forgetting of pre-trained knowledge or inefficient credit assignment during preference learning.

In this paper, we challenge the monolithic alignment paradigm and propose Hierarchical Alignment, a surgical fine-tuning framework that respects the anatomical hierarchy of Transformers. By partitioning the model into three functionally motivated blocks—*Local* (shallow), *Intermediate* (middle), and *Global* (deep)—we apply targeted DPO updates via Low-Rank Adaptation (LoRA). This structured approach allows us to investigate a fundamental question: *Where does alignment actually happen?* If the model's internal representations evolve from surface-level tokens to abstract concepts, then preference optimization should, in theory, yield distinct behavioral shifts depending on which functional block is engaged.

To empirically validate this hypothesis, we conduct a systematic study across four state-of-the-art model families: Llama-2-7B, Llama-3.1-8B, Qwen2.5-7B, and Qwen3-8B. Moving beyond aggregate win rates—which often mask nuanced model behaviors—we implement a granular LLM-as-Judge protocol. Using Qwen3-Max as an impartial evaluator, we score model outputs across 16 high-resolution quality dimensions, ranging from syntactic complexity and logical flow to ethical sensitivity and knowledge depth.

Our investigation yields several counter-intuitive findings that challenge prevailing assumptions in model tuning. First, we demonstrate that *Mid-Align* consistently matches or even surpasses the performance of full-parameter DPO, particularly in reasoning-heavy models like Qwen2.5-7B. This identifies the middle layers as the "critical nexus"

for alignment, where preference signals are most effectively integrated into semantic representations. Second, we find that Global-Align (updating only the final layers) significantly underperforms, suggesting a bottom-up representational dependency: high-level reasoning cannot compensate for misaligned mid-level logic. Finally, we show that hierarchical strategies induce predictable behavioral shifts—*Local-Align* sharpens instruction-following and fluency, while *Mid-Align* bolsters logical depth and coherence.

Our contributions are three-fold: we formalize Hierarchical Alignment as a framework that shifts the alignment focus from monolithic updates to architecture-aware, surgical interventions; we provide empirical evidence that Intermediate Block updates are the primary drivers of effective preference learning, offering a path toward extreme parameter efficiency without performance degradation; and we demonstrate that pre-training quality and model architecture critically modulate alignment outcomes, advocating for a shift toward interpretable and controllable model editing rather than brute-force tuning.By replacing the sledgehammer of monolithic alignment with the scalpel of hierarchical intervention, we propose a paradigm that works with the model's inherent structure rather than against it.

2 Related Work

Our work lies at the intersection of model alignment, modular editing, and architectural interpretability. While existing approaches have made significant progress in aligning large language models (LLMs) with human preferences, they often treat the model as a monolithic entity. In contrast, we argue that effective alignment must account for the internal functional hierarchy of Transformers—a principle increasingly supported across NLP, vision, and even non-text domains. This section synthesizes recent advances along three dimensions: (1) evolution of alignment paradigms, (2) emergence of modular and targeted editing strategies, and (3) cross-domain evidence for hierarchical structure in deep networks.

2.1 The Evolution of Alignment Paradigms

Modern LLM alignment has evolved from Supervised Fine-Tuning (SFT) to reinforcement learning frameworks like RLHF (Ouyang et al., 2022), and more recently to simplified alternatives such as Direct Preference Optimization (DPO) (Rafailov et al., 2024). These methods aim to improve helpfulness, honesty, and harmlessness by learning from preference data. Recent studies highlight the complementary strengths of different approaches: Pant (2025) show that combining SFT and DPO yields superior performance on safety and helpfulness metrics compared to either method alone, underscoring the value of hybrid pipelines.

Further innovations seek to unify the advantages of multiple paradigms. Wang et al. (2025a) propose GRAO, a framework that integrates SFT and reinforcement learning through group-level relative advantage weighting, achieving substantial gains over DPO, PPO, and GRPO baselines. Meanwhile, Li et al. (2025) survey the role of RL in agentic systems, noting that while DPO is off-policy and weak in long-horizon credit assignment, reinforcement learning enables closed-loop optimization crucial for complex reasoning and tool use.

Despite their differences, most current alignment methods—including DPO and its variants—apply global updates across all model parameters. This monolithic paradigm ignores the possibility of structurally informed interventions. Even multilingual alignment techniques like CM-Align (Zhang et al., 2025b), which improves cross-lingual consistency by filtering noisy preference pairs, still operate under this uniform update assumption. Our work challenges this default by asking: can we make alignment itself more structured?

2.2 Modular and Targeted Editing: From Black-Box Modules to Internal Structure

A growing trend in model editing advocates for fine-grained control rather than whole-model tuning. One line of work introduces external plug-and-play modules to inject specific behaviors without modifying the base model. For example, ALIGNER uses lightweight adapters for value-specific alignment (Ji et al., 2024), while MODULAR PLURALISM composes small experts for context-sensitive control (Feng et al., 2024). These approaches demonstrate that modularity enhances efficiency and flexibility.

Beyond external modules, recent efforts explore internal structural interventions. Hu et al. (2021) propose LoRA-based methods restrict updates to low-rank subspaces. However, these remain largely architectural or parameter-efficient—they do not necessarily engage with the semantic function of different network components.

Notably, similar ideas have emerged in multimodal and specialized domains. In text-to-image generation, Zhang et al. (2025a) analyze DiT models and find a hierarchical layer response: early layers focus on instances, middle layers on background, late layers on attributes. Based on this, they design AST, a training-free method that tunes attention maps layer-by-layer to enhance multi-instance synthesis. Similarly, Zeng et al. (2025) address imbalanced responsibilities in image editing by assigning "design" tasks to a frozen understanding module (Qwen-VL), effectively creating a two-tier system where high-level planning guides low-level generation.

In vision-language models, Wang et al. (2025b) introduce V-SEAM, a framework that performs concept-level visual editing by identifying attention heads contributing to object, attribute, and relationship predictions—revealing a semantic hierarchy within the model's internal mechanisms. Meanwhile, Zhao et al. (2025) propose LatHAdapter, which leverages latent hierarchical structure in few-shot classification by projecting categories and images into hyperbolic space, enabling richer modeling of one-to-many associations.

Even outside NLP, hierarchical decomposition proves powerful. Yao et al. (2025) tackle bug signal dilution in Verilog debugging by splitting modules into semantically coherent fragments, showing that localized repair significantly outperforms end-to-end correction. This mirrors our hypothesis: narrowing the scope of intervention improves precision and effectiveness.

These works collectively suggest a paradigm shift—from holistic tuning to **structured, scoped, and function-aware editing**—yet none apply this principle directly to the layer-wise functional specialization of LLMs during alignment.

2.3 Cross-Domain Evidence for Hierarchical Organization in Deep Networks

The idea that deep networks organize knowledge hierarchically is not new, but recent work provides increasingly granular evidence across modalities.

In computer vision, Olson et al. (2025) use Sparse Autoencoders (SAEs) to probe DINOv2 and find that its representations implicitly encode the ImageNet taxonomy, with deeper layers refining class-specific information. This suggests that vision models naturally develop ontological hierarchies during training. Similarly, Zhu and Cangelosi (2025) extend activation maximization to intermediate layers of CNNs and ViTs, revealing how features evolve from edges to objects across the network depth.

In language modeling, probing studies confirm a clear division of labor: lower layers capture syntax and morphology, while upper layers handle semantics and reasoning (van Aken et al., 2019). This pattern persists in instruction-tuned models, where early layers preserve general linguistic knowledge, middle layers integrate context, and final layers execute task-specific logic (Nadipalli, 2025). Even in state-space models like Mamba, causal tracing shows factual recall occurs in mid-layers, while output coherence is managed later (Sharma et al., 2024).

Structural priors are also exploited in other symbolic tasks. For Chinese character recognition, Zhu et al. (2025) propose Hi-GITA, a framework that models strokes, radicals, and characters at multiple granularities, demonstrating that explicit hierarchical representation significantly boosts zero-shot accuracy. In energy-constrained settings, Vahdatpour et al. (2025) decompose neural networks into two tiers: lower layers optimized via FPGA-based equation solving for efficient feature extraction, and upper layers updated incrementally for adaptive decision-making—forming a Compound LLM framework that reduces computational cost while maintaining performance.

Together, these findings across vision, language, hardware, and symbol processing establish a compelling pattern: **deep networks naturally develop—and can be better controlled through—hierarchical organization**.

2.4 Positioning Our Work

While many recent works recognize structure—whether in attention maps, adapter design, or system architecture—few leverage it for **preference-based alignment**. Most still apply DPO or RLHF uniformly across the entire model.

Our work fills this gap by introducing **Hierarchical Alignment**, a framework that partitions the Transformer into functionally distinct blocks (Local, Intermediate, Global) and applies targeted DPO via LoRA to each. Unlike external modular systems (Zeng et al., 2025; Feng et al., 2024) or fragmented debugging (Yao et al., 2025), we intervene within the model's internal layer hierarchy. Unlike hierarchical adapters in vision (Zhao et al., 2025) or attention tuning in DiT (Zhang et al., 2025a), we apply this principle to *behav-

ioral alignment in LLMs.

Despite these advances, none have systematically explored whether aligning functionally distinct layer blocks leads to predictable, controllable improvements in preference learning—a gap our work directly addresses.

By grounding our method in both empirical probing results and cross-domain design principles, we provide a unified, interpretable, and efficient path toward more controllable language models—one that respects not just what LLMs do, but how they do it.

3 Methodology

This section operationalizes the Hierarchical Alignment framework. We first establish its theoretical underpinnings through formal definitions and core hypotheses. We then detail the implementation, specifying how Direct Preference Optimization (DPO) and Low-Rank Adaptation (LoRA) are employed for targeted updates. The section culminates in a precise algorithmic specification and a set of testable predictions that directly guide our experimental validation.

3.1 Theoretical Foundations

Our approach is built upon the principle that a Transformer's internal architecture is not monolithic but functionally stratified. We formalize this as follows.

Definition 1 (Functional Stratification)**.** *Let a Transformer model be a sequence of N layers, $\mathcal{T} = \{L_1, L_2, \ldots, L_N\}$. A **functional stratification** is a partition of these layers into K disjoint blocks, $\Pi = \{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_K\}$, where each block $\mathcal{S}_k = \{L_i : i \in I_k\}$ is hypothesized to perform a distinct functional role. The model's global computation F can thus be viewed as a composition of block-specific functions: $F(\mathbf{x}; \Theta) = f_K \circ f_{K-1} \circ \cdots \circ f_1(\mathbf{x})$.*

This framework rests on two foundational hypotheses derived from extensive interpretability research.

Hypothesis 1 (Functional Specialization)**.** *In a sufficiently pre-trained LLM, a natural functional stratification exists where blocks process information hierarchically. This hierarchy manifests as a progression from lower-level linguistic features (e.g., syntax) in initial blocks to higher-level semantic and reasoning capabilities (e.g., factuality, intent) in final blocks.*

Hypothesis 2 (Objective-Function Correspondence)**.** *For a given alignment objective a_m (e.g., improving factuality) with a corresponding loss ℓ_m, the loss gradient is predominantly concentrated within the parameter subspace Θ_k of the functionally corresponding block $\mathcal{S}_k$. Formally:*

$$\mathbb{E}_{\mathbf{x}\sim\mathcal{D}} \left\| \frac{\partial \ell_m(\mathbf{x})}{\partial \Theta_k} \right\| \gg \mathbb{E}_{\mathbf{x}\sim\mathcal{D}} \left\| \frac{\partial \ell_m(\mathbf{x})}{\partial \Theta_{k'}} \right\|, \quad \forall k' \neq k$$

This hypothesis provides the theoretical justification for targeted intervention, suggesting that surgical updates to a specific block will be maximally effective for its corresponding objective while minimizing collateral effects on others.

3.2 Implementation

We translate the theoretical framework into a concrete algorithm by specifying the block partitioning scheme, the alignment loss, and the mechanism for targeted parameter updates.

3.2.1 Functional Block Partitioning

Guided by Hypothesis 1, we instantiate the stratification Π with three functionally motivated blocks:

- **Local Block ($\mathcal{S}_{\text{local}}$):** The initial one-third of layers, responsible for syntax, grammar, and fluency.
- **Intermediate Block ($\mathcal{S}_{\text{mid}}$):** The middle one-third of layers, governing discourse coherence and local semantic consistency.
- **Global Block ($\mathcal{S}_{\text{global}}$):** The final one-third of layers, handling thematic relevance, instruction adherence, and high-level reasoning.

To ensure model agnosticism and reproducibility, we employ a simple partitioning heuristic. Given N layers, the block sizes are determined systematically to distribute layers as evenly as possible. This heuristic provides a strong, non-arbitrary baseline for our experiments.

3.2.2 Alignment Objective: Direct Preference Optimization (DPO)

We adopt the DPO loss as our alignment objective. For a preference tuple (x, y_w, y_l) where response y_w is preferred over y_l for prompt x, the loss is

Table 1: Model groups and alignment strategies.

Group Name	Strategy	Description
`Base Model`	None	Original SFT model; serves as baseline.
`Full-DPO`	Monolithic	LoRA applied to all layers; standard DPO baseline.
`Local-Align`	Hierarchical	Only Local Block updated.
`Mid-Align`	Hierarchical	Only Intermediate Block updated.
`Global-Align`	Hierarchical	Only Global Block updated.

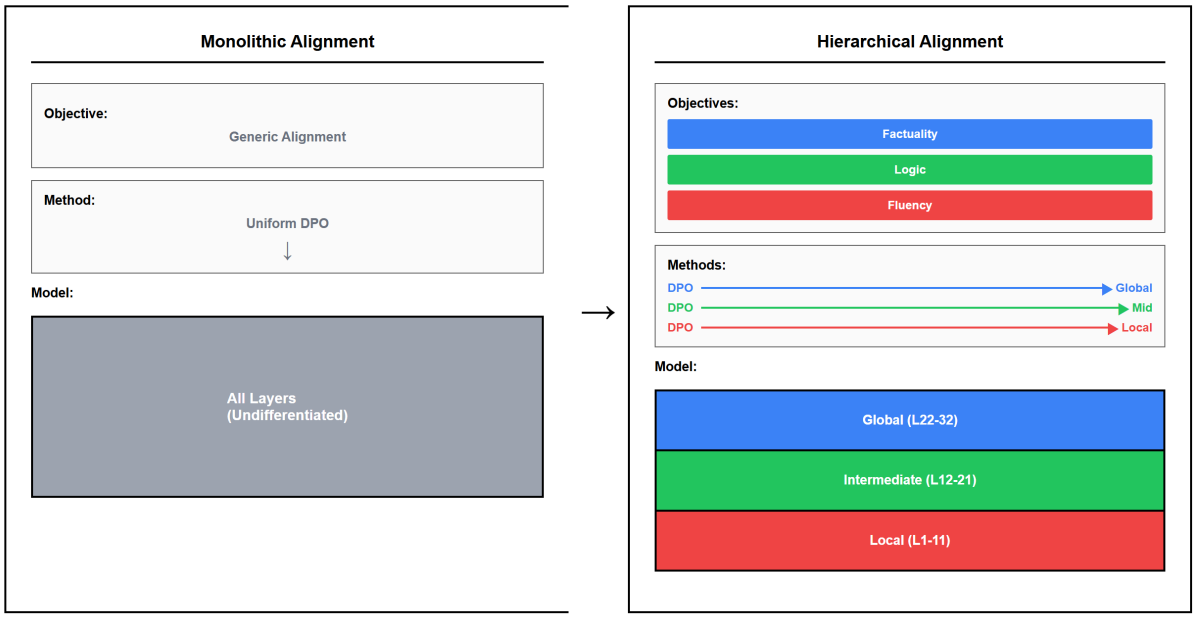

Figure 1: **Theoretical framework.** *Left: Monolithic Alignment* applies a uniform DPO update to all layers, treating the model as undifferentiated and risking an *alignment tax* (e.g., fluency improves while logic degrades). *Right: Hierarchical Alignment* decomposes objectives (grammar/fluency, coherence/logic, factuality/reasoning) and performs targeted optimization on functionally specialized blocks (local, intermediate, global), reducing interference and improving controllability.

defined as:

$$\mathcal{L}_{\text{DPO}} = -\,\mathbb{E}\left[\log\sigma\left(\beta\log\frac{\pi_\theta(y_w|x)}{\pi_{\text{ref}}(y_w|x)} - \beta\log\frac{\pi_\theta(y_l|x)}{\pi_{\text{ref}}(y_l|x)}\right)\right] \tag{1}$$

where π_θ is the policy model being optimized, π_{ref} is a frozen reference model, and β is a temperature parameter.

3.2.3 Targeted Updates via Low-Rank Adaptation (LoRA)

To enforce the principle of targeted intervention from Hypothesis 2, we require a mechanism that confines parameter updates to a specific block $\mathcal{S}_k$. We employ LoRA for this purpose, treating it as a **subspace selector**.

Specifically, we freeze the entire base model and inject trainable, low-rank matrices *exclusively* into the self-attention modules of the layers within the target block $\mathcal{S}_k$. This design choice is deliberate: self-attention is the primary mechanism for information integration and representation refinement within the Transformer architecture. By modifying it directly, we aim to precisely control *how* information is processed within a functional block, while preserving the vast world knowledge typically stored in the feed-forward network (FFN) parameters.

The optimization thus operates not on the full parameter space Θ, but only on the LoRA parameters $\Theta_{k,\text{LoRA}}$ associated with block $\mathcal{S}_k$. The update

rule becomes:

$$\Theta_{k,\text{LoRA}}^{(t+1)} \leftarrow \Theta_{k,\text{LoRA}}^{(t)} - \eta \nabla_{\Theta_{k,\text{LoRA}}} \mathcal{L}_{\text{DPO}} \quad (2)$$

The *Hierarchical Alignment* framework operationalizes the principle of functional stratification, shifting LLM tuning from monolithic updates to architecture-aware, surgical interventions. This approach is grounded in the *Functional Specialization Hypothesis*, which posits that Transformer layers are organized into a hierarchical progression—moving from low-level linguistic features in shallow layers to high-level semantic integration and reasoning in deeper blocks. By formalizing this hierarchy through the *Objective-Function Correspondence* hypothesis, we argue that alignment signals are most effectively integrated when targeted at the parameter subspaces responsible for specific cognitive tasks, thereby reducing the "alignment tax" and improving model controllability.

To empirically test this framework, we decompose the model into three functionally motivated segments—Local, Intermediate, and Global—and utilize Direct Preference Optimization (DPO) as the primary alignment objective. Implementation is achieved through Low-Rank Adaptation (LoRA), which serves as a subspace selector to confine parameter updates exclusively to the self-attention modules within a targeted block. This design choice precisely modulates how information is processed within a specific functional region while preserving the broad world knowledge stored in the frozen feed-forward networks, establishing a systematic and interpretable path for fine-grained behavioral editing in large language models.

4 Experiment

This section presents a comprehensive evaluation of *Hierarchical Alignment* across four representative large language models: *Llama-2-7B*, *Llama-3.1-8B*, *Qwen2.5-7B*, and *Qwen3-8B*. Our investigation focuses on how targeted updates to functionally specialized layer blocks influence alignment outcomes compared to monolithic tuning. We first outline our experimental configuration and the multidimensional evaluation framework used to dissect model behavior.

4.1 Experimental Setup and Evaluation Metrics

Experimental Design Our study employs a controlled design utilizing a 10k-sample training subset and a 1k-sample held-out evaluation set from the *Anthropic/hh-rlhf* dataset. To isolate the effects of hierarchical specialization, we compare five distinct conditions for each model: (1) the untrained `Base` model; (2) a monolithic `Full-DPO` baseline; and our proposed hierarchical strategies: (3) `Local-Align`, (4) `Mid-Align`, and (5) `Global-Align`, each applying targeted DPO updates to specific blocks via LoRA. To ensure a rigorous comparison, we maintain identical hyperparameters across all experimental runs, the details of which are provided in Appendix B.

Multidimensional Evaluation Protocol To move beyond aggregate win rates, we implement a granular *LLM-as-Judge* framework using *Qwen3-Max* as an impartial evaluator. Model responses are scored across 16 dimensions grouped into six functional categories: Model responses are evaluated across 16 dimensions grouped into six functional categories: (1) *Language Quality* (grammar, fluency, token robustness, conciseness); (2) *Logic & Coherence* (logical flow, consistency); (3) *Content Quality* (factuality, depth, cross-domain, creativity); (4) *Safety & Ethics*; (5) *Task Execution* (instruction following, tone); and (6) *Meta-Level* (reflection, utility).

All evaluations utilize a 5-point Likert scale anchored to a fixed baseline response (rated at 3/5). This structured scoring allows for a high-resolution analysis of how specific alignment strategies modulate distinct capabilities. Detailed prompts, dimension definitions, and output templates are provided in Appendix D to ensure full reproducibility.

4.2 Main Results and Analysis

This section presents a comprehensive evaluation of our hierarchical alignment strategies, transitioning from macro-level performance metrics to granular behavioral insights. Our findings reveal the distinct functional roles of layer blocks and highlight the critical influence of pre-training quality on alignment efficacy.

4.2.1 Alignment Efficacy and Behavioral Specialization

Macro-level Performance Comparison We first analyze the *Overall* score, a holistic assessment of response quality anchored to a fixed baseline (rated 3). As summarized in Table 2, monolithic *Full-DPO* achieves the highest aggregate mean (3.067), followed closely by *Local-Align* (3.013) and *Mid-Align* (3.002). Notably, *Global-Align* is the only

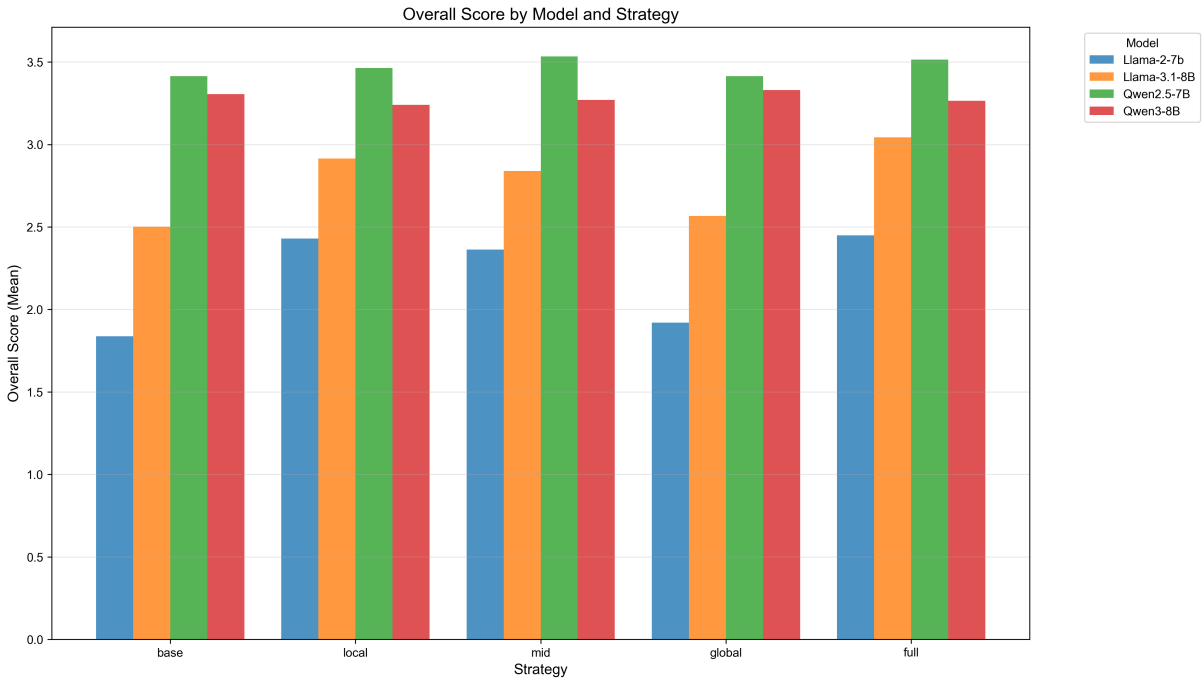

Figure 2: Overall score comparison across models and strategies. Error bars denote standard deviation. Qwen2.5-7B shows superior performance across all alignment methods.

trained strategy that underperforms the baseline (2.808), suggesting that updates restricted to deep layers are insufficient for robust preference alignment.

However, aggregate metrics mask critical inter-model variation. As shown in Table 3, *Qwen2.5-7B* consistently dominates the rankings across all strategies. Remarkably, its *Mid-Align* configuration achieves a score of 3.534—surpassing even its own *Full-DPO* result (3.514) while updating significantly fewer parameters. This evidence suggests that for high-quality foundation models, surgical alignment at the intermediate functional bottleneck can be more efficient than monolithic tuning.

Table 2: Average Overall scores by strategy ($N = 4,000$).

Strategy	*Mean*	*Std*	*Median*	*Count*
Base	2.765	1.340	3.000	4,000
Local	3.013	1.269	3.000	4,000
Mid	3.002	1.273	3.000	4,000
Global	2.808	1.338	3.000	4,000
Full	3.067	1.253	3.000	4,000

Fine-Grained Behavioral Shifts To dissect how specific blocks modulate model behavior, we examine 15 sub-dimensions via the heatmap visualization in Figure 3. Several predictable patterns emerge based on the targeted block:

(1) *Language Quality*: Updates to the *Local Block* (shallow layers) primarily sharpen fluency, *Conciseness*, and *TokenRobustness*, confirming the role of early layers in lexical control. (2) *Logic & Coherence*: Contrary to the intuition that reasoning resides in deep layers, *Mid-Align* consistently yields the strongest gains in *CoherenceLogic* and *TopicCoherence*, particularly for *Qwen2.5-7B*. This identifies intermediate layers as the critical nexus for discourse structuring. (3) *Content Quality*: *Mid-Align* similarly enhances *KnowledgeDepth* and cross-domain applicability, suggesting that mid-layers manage schema-like knowledge integration. (4) *Task Execution*: *InstructionFollowing* benefits most from *Full-DPO* and *Local-Align*, implying that prompt interpretation begins at the initial representational stages.

Safety, Ethics, and Model Resilience Across all conditions, *Safety* and *EthicsSensitivity* scores remain consistently high (> 4.0), even in untrained *Base* models. This indicates that ethical priors are deeply internalized during pre-training and remain resilient to post-hoc alignment strategies. Furthermore, the fact that the *Qwen2.5-7B* base model (Rank 4) outperforms many fine-tuned variants of larger models underscores that foundation model quality sets a performance ceiling that post-hoc alignment can refine but not fundamentally rewrite.

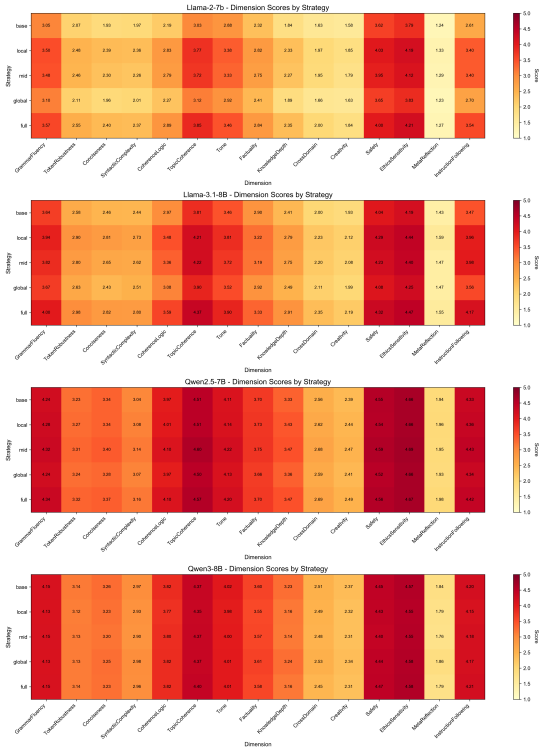

Figure 3: Heatmap of average scores across 15 evaluation dimensions, grouped by model and strategy. Color intensity reflects score magnitude (light yellow = low, dark red = high). This fine-grained visualization reveals the predictable behavioral shifts induced by hierarchical interventions.

Table 3: Top 10 Model-Strategy combinations by mean Overall score ($N = 1,000$).

Rank	*Model*	*Strategy*	*Mean*
1	Qwen2.5-7B	Mid	3.534
2	Qwen2.5-7B	Full	3.514
3	Qwen2.5-7B	Local	3.462
4	Qwen2.5-7B	Base	3.414
5	Qwen2.5-7B	Global	3.413
6	Qwen3-8B	Global	3.329
7	Qwen3-8B	Base	3.306
8	Qwen3-8B	Mid	3.270
9	Qwen3-8B	Full	3.264
10	Qwen3-8B	Local	3.240

5 Limitations

Our findings are based on four LLMs with similar architectures—results may not generalize to models with different designs (e.g., state-space or retentive networks). The layer partitioning is depth-based and static, which may not reflect functional roles; future work could use probing or gradient analysis for dynamic block assignment. Evaluation relies on an LLM-as-Judge (`Qwen3-Max`), which, despite structured prompting, may inherit biases and cannot fully substitute human judgment. Finally, all experiments use a fixed DPO configuration; optimal hyperparameters may vary across blocks and models. These limitations suggest opportunities for more adaptive, interpretable, and robust hierarchical alignment methods.

6 Ethical Considerations

Our work raises several ethical considerations. First, the Anthropic/hh-rlhf dataset may contain social biases related to gender, race, or ideology, which could be amplified during alignment—even if not introduced by our method. Second, while our approach improves parameter efficiency, training and evaluation still demand significant computational resources; we encourage future work on lightweight replications to improve accessibility. Third, layer-specific tuning enables fine-grained behavioral control, posing dual-use risks: such techniques could be misused to induce harmful behaviors while maintaining fluent output. We advocate for transparency in model editing and research into detection mechanisms for stealthy manipulations. Finally, our LLM-as-Judge evaluation uses Qwen3-Max, whose training data and biases are not fully transparent. We caution against overreliance on automated metrics and recommend human validation for high-stakes applications.

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References

Shangbin Feng, Taylor Sorensen, Yuhan Liu, Jillian Fisher, Chan Young Park, Yejin Choi, and Yulia Tsvetkov. 2024. Modular pluralism: Pluralistic alignment via multi-llm collaboration. *Preprint*, arXiv:2406.15951.

Edward J. Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *Preprint*, arXiv:2106.09685.

Jiaming Ji, Boyuan Chen, Hantao Lou, Donghai Hong, Borong Zhang, Xuehai Pan, Juntao Dai, Tianyi Qiu, and Yaodong Yang. 2024. Aligner: Efficient alignment by learning to correct. *Preprint*, arXiv:2402.02416.

Wenjun Li, Zhi Chen, Jingru Lin, Hannan Cao, Wei Han, Sheng Liang, Zhi Zhang, Kuicai Dong, Dexun Li, Chen Zhang, and Yong Liu. 2025. Reinforcement learning foundations for deep research systems: A survey. *Preprint*, arXiv:2509.06733.

Suneel Nadipalli. 2025. Layer-wise evolution of representations in fine-tuned transformers: Insights from sparse autoencoders. *Preprint*, arXiv:2502.16722.

Matthew Lyle Olson, Musashi Hinck, Neale Ratzlaff, Changbai Li, Phillip Howard, Vasudev Lal, and Shao-Yen Tseng. 2025. Analyzing hierarchical structure in vision models with sparse autoencoders. *Preprint*, arXiv:2505.15970.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. 2022. Training language models to follow instructions with human feedback. *Preprint*, arXiv:2203.02155.

Piyush Pant. 2025. Improving llm safety and helpfulness using sft and dpo: A study on opt-350m. *Preprint*, arXiv:2509.09055.

Rafael Rafailov, Archit Sharma, Eric Mitchell, Stefano Ermon, Christopher D. Manning, and Chelsea Finn. 2024. Direct preference optimization: Your language model is secretly a reward model. *Preprint*, arXiv:2305.18290.

Arnab Sen Sharma, David Atkinson, and David Bau. 2024. Locating and editing factual associations in mamba. *Preprint*, arXiv:2404.03646.

Mohammad Saleh Vahdatpour, Huaiyuan Chu, and Yanqing Zhang. 2025. The energy-efficient hierarchical neural network with fast fpga-based incremental learning. *Preprint*, arXiv:2509.15097.

Betty van Aken, Benjamin Winter, Alexander Löser, and Felix A. Gers. 2019. How does bert answer questions?: A layer-wise analysis of transformer representations. In *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*, CIKM '19, page 1823–1832. ACM.

Haowen Wang, Yun Yue, Zhiling Ye, Shuowen Zhang, Lei Fan, Jiaxin Liang, Jiadi Jiang, Cheng Wei, Jingyuan Deng, Xudong Han, Ji Li, Chunxiao Guo, Peng Wei, Jian Wang, and Jinjie Gu. 2025a. Learning to align, aligning to learn: A unified approach for self-optimized alignment. *Preprint*, arXiv:2508.07750.

Qidong Wang, Junjie Hu, and Ming Jiang. 2025b. V-seam: Visual semantic editing and attention modulating for causal interpretability of vision-language models. *Preprint*, arXiv:2509.14837.

Bingkun Yao, Ning Wang, Xiangfeng Liu, Yuxin Du, Yuchen Hu, Hong Gao, Zhe Jiang, and Nan Guan. 2025. Arsp: Automated repair of verilog designs via semantic partitioning. *Preprint*, arXiv:2508.16517.

Ziyun Zeng, Junhao Zhang, Wei Li, and Mike Zheng Shou. 2025. Draw-in-mind: Learning precise image editing via chain-of-thought imagination. *Preprint*, arXiv:2509.01986.

Chunyang Zhang, Zhenhong Sun, Zhicheng Zhang, Junyan Wang, Yu Zhang, Dong Gong, Huadong Mo, and Daoyi Dong. 2025a. Hierarchical and step-layer-wise tuning of attention specialty for multi-instance synthesis in diffusion transformers. *Preprint*, arXiv:2504.10148.

Xue Zhang, Yunlong Liang, Fandong Meng, Songming Zhang, Yufeng Chen, Jinan Xu, and Jie Zhou. 2025b. Cm-align: Consistency-based multilingual alignment for large language models. *Preprint*, arXiv:2509.08541.

Yumiao Zhao, Bo Jiang, Yuhe Ding, Xiao Wang, Jin Tang, and Bin Luo. 2025. Fine-grained vlm fine-tuning via latent hierarchical adapter learning. *Preprint*, arXiv:2508.11176.

Hongbo Zhu and Angelo Cangelosi. 2025. Representation understanding via activation maximization. *Preprint*, arXiv:2508.07281.

Yinglian Zhu, Haiyang Yu, Qizao Wang, Wei Lu, Xiangyang Xue, and Bin Li. 2025. Zero-shot chinese character recognition with hierarchical multi-granularity image-text aligning. *Preprint*, arXiv:2505.24837.

A Model Layer Partition Details

To ensure reproducibility and cross-architecture generalizability, we implement a *dynamic layer splitting* strategy that partitions each Transformer model into three functionally distinct blocks: Local, Intermediate, and Global. Given a total depth N, we define the base layers per block as $n = N \,//\, 3$ and the remainder as $r = N \bmod 3$. The blocks are then sequentially allocated such that the Local Block comprises the first $n + [r > 0]$ layers, the Intermediate Block covers the subsequent $n + [r > 1]$ layers, and the Global Block contains the remaining layers, where $[\cdot]$ denotes the Iverson bracket. The specific layer indices for each evaluated model are detailed in Table 4. All LoRA adapters are applied exclusively within these predefined ranges to ensure a rigorous and isolated comparison of hierarchical alignment effects.

Note that layer indexing starts at 0. For example, in Qwen2.5-7B ($N = 28$), $n = 9$, $r = 1$, so only the Local Block receives an extra layer.

This systematic approach ensures consistent methodology across models of varying depths, enabling fair comparison of hierarchical alignment strategies.

B Complete Training Hyperparameters

We provide the full list of hyperparameters used in our Direct Preference Optimization (DPO) training pipeline to guarantee reproducibility. Unless otherwise specified, all models and conditions share the same training configuration.

All experiments were conducted using the Hugging Face `Transformers` and `TRL` libraries, with consistent random seeds for data loading, shuffling, and parameter initialization.

C Additional Training Efficiency Results

We begin by analyzing the optimization behavior during Direct Preference Optimization (DPO) across all models and strategies. Figure 4 displays the training loss curves for each model-strategy combination, with one subplot per base model. All configurations converge within a single epoch, indicating sufficient data exposure and stable optimization under our hyperparameter setup (see Appendix B).

For clarity and readability, detailed training metrics—including full loss curves, final loss comparisons, and training time measurements—are reported in Appendix C. These results confirm stable optimization across all configurations and reveal efficiency differences among strategies, which inform our interpretation of downstream evaluation outcomes.

As shown in both the aggregate view (Figure 4) , all fine-tuned variants (*local*, *mid*, *global*, *full*) exhibit consistent and monotonic reduction in DPO loss, while the base models (no training) maintain flat or undefined loss trajectories.

In addition to model performance, we evaluate the computational efficiency of each alignment strategy by measuring the total wall-clock training time for one epoch across all Model-Strategy combinations. This analysis provides insight into the practical trade-offs between parameter efficiency, model size, and real-world deployment cost.

Figure 5 presents a grouped bar chart comparing training times (in minutes) across strategies and models. All experiments were conducted on identical hardware configurations (1× NVIDIA A100 GPUs, full bfloat16 precision, gradient checkpointing enabled), ensuring fair comparison.

D Detailed Evaluation Protocol

To ensure transparency, consistency, and full reproducibility of our automated evaluation process, we provide the complete structured prompt used to elicit judgments from the *Qwen3-Max* model. This protocol enforces a blind evaluation, anchors scoring to a fixed reference point, and mandates a strict machine-readable output format.

Evaluation Dimensions Table 6 details the 16 specialized dimensions used for scoring. Each dimension is designed to capture specific linguistic, logical, or ethical attributes of the generated responses.

LLM-as-Judge Prompt Template The evaluation prompt provided to *Qwen3-Max* is structured as follows. We use a Likert-scale approach (1–5) where a score of 3 is explicitly anchored to a mediocre baseline case to minimize model-specific bias.

> ***[System Role]***
> *You are a rigorous and objective text quality analyst. Your task is to evaluate a single AI-generated response based on predefined dimensions and scoring standards, anchored to a baseline example.*
>
> ***[Baseline Case (Anchor for Score = 3)]***
> *- Prompt: What are some good types of hats to shade myself from the sun?*
> *- Response: There are many kinds of hats, like*

Table 4: Layer partitioning for each model under the dynamic splitting strategy.

Model	Total Layers	Local Block	Intermediate Block	Global Block
Llama-2-7b	32	0–10	11–21	22–31
Llama-3.1-8B	32	0–10	11–21	22–31
Qwen3-8B	36	0–11	12–23	24–35
Qwen2.5-7B	28	0–9	10–18	19–27

Table 5: Complete set of training hyperparameters.

Hyperparameter	Value
Learning Rate	1.0×10^{-5}
Optimizer	AdamW
Weight Decay	0.01
β_1, β_2	0.9, 0.999
Batch Size	6
Gradient Accumulation Steps	4
Number of Epochs	1
DPO Beta (β)	0.1
LoRA Rank (r)	16
LoRA Alpha (α)	32
LoRA Dropout	0.05
Target Modules	q_proj, k_proj, v_proj, o_proj
Precision	bfloat16
Gradient Checkpointing	Enabled
Max Sequence Length	2048
Seed (for data)	42

baseball caps, sun hats, bucket hats and so on. You can choose one you like.

[Dimension Definitions]
(The dimensions defined in Table 6 are passed here in JSON format...)

[Scoring Criteria (Relative to Baseline)]
- 1: Significantly worse than baseline (severe factual errors or topic drift).
- 2: Slightly worse than baseline (minor shortcomings in logic or content).
- 3: On par with baseline (meets minimum requirements, lacks refinement).
- 4: Slightly better than baseline (improved detail or structure).
- 5: Clearly superior to baseline (substantial enhancement in multiple dimensions).

[Response to Evaluate]
- User Prompt: [INSERT PROMPT]
- Model Response: [INSERT RESPONSE]

[Output Requirements]
*Return a JSON array where each element contains "dimension", "score" (integer 1-5), and "reason". Output **only** the raw JSON array.*

Table 6: Definitions of the 16 evaluation dimensions grouped by functional categories.

Dimension	Definition
GrammarFluency	Grammatical accuracy, sentence completeness, and general fluency.
TokenRobustness	Consistency in semantic integrity across input variations.
Conciseness	Balance between brevity and information completeness.
SyntacticComplexity	Diversity of syntactic structures and linguistic richness.
CoherenceLogic	Logical flow and causal relationships between sentences.
TopicCoherence	Relevance and focus on the central query themes.
Tone	Contextual appropriateness of the response style.
Factuality	Empirical accuracy of claims and information.
KnowledgeDepth	Detail level, including material properties or design features.
CrossDomain	Generalizability across diverse scenarios (e.g., sports, urban).
Creativity	Novelty and originality of the proposed suggestions.
Safety	Absence of hazardous advice or high-risk content.
EthicsSensitivity	Adherence to ethical norms and exclusionary-free language.
MetaReflection	Self-awareness and explicit statement of guidance limitations.
InstructionFollowing	Degree to which the user's specific constraints are addressed.
Overall	Holistic quality assessment synthesized across all dimensions.

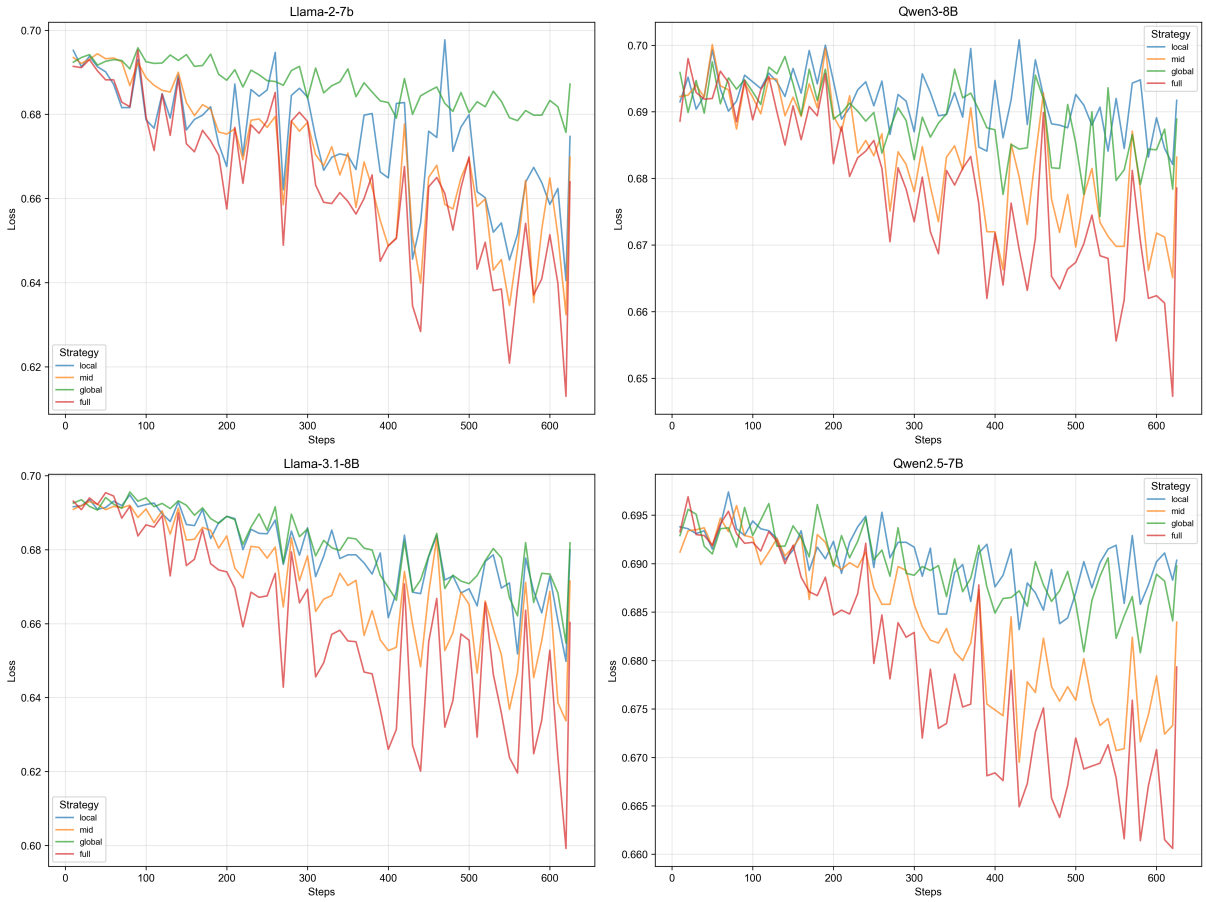

Figure 4: Training loss curves across all models and strategies. Each subplot corresponds to one base model, showing loss evolution over training steps.

Figure 5: Total training time (in minutes) per Model-Strategy combination. Bars are grouped by strategy, with each color representing a different base model.