Fluid Reasoning Representations

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Abstract

Reasoning language models, which generate long chains of thought, dramatically outperform non-reasoning language models on abstract problems. However, the internal model mechanisms that allow this superior performance remain poorly understood. We present a mechanistic analysis of how QwQ-32B – a model specifically trained to produce extensive reasoning traces – process abstract structural information. On Mystery Blocksworld – a semantically obfuscated planning domain – we find that QwQ-32B gradually improves its internal representation of actions and concepts during reasoning. The model develops abstract encodings that focus on structure rather than specific action names. Through steering experiments, we establish causal evidence that these adaptations improve problem solving: injecting refined representations from successful traces boosts accuracy, while symbolic representations can replace many obfuscated encodings with minimal performance loss. We find that one of the factors driving reasoning model performance is in-context refinement of token representations, which we dub *Fluid Reasoning Representations*.

1 Introduction

A fundamental question in understanding reasoning language models is whether these models merely pattern-match against memorized associations, or whether they can dynamically construct new representations during problem-solving. This distinction is critical: true reasoning requires adapting internal representations to fit novel problem structures, not just retrieving precomputed solutions. Several reasoning benchmarks have been introduced to assess whether language models exhibit genuine reasoning capabilities or rely primarily on memorized patterns. For instance, ARC-AGI series of benchmarks (Chollet et al., 2025; Chollet, 2019) test fluid intelligence through novel visual reasoning tasks designed to minimize reliance on prior knowledge and require genuine abstraction and problem-solving capabilities.

PlanBench (Valmeekam et al., 2023) takes a complementary approach by creating semantically obfuscated versions of classical planning problems. A particular example is BlocksWorld, a simple planning domain where models must rearrange blocks by applying actions like "pick up" and "put down" according to explicit rules. These action names appear frequently in pretraining corpora with semantics closely aligned to BlocksWorld, enabling even moderately-sized models to solve standard problems with 60-70% accuracy by leveraging preexisting associations. It's obfuscated counterpart – Mystery BlocksWorld breaks these associations while preserving logical structure: all predicates and actions are replaced with semantically unrelated words (e.g., "pick up" becomes attack", "on top of" becomes "craves"). This isolates structural reasoning from pattern-matching –

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success requires inferring obfuscated terms from context and constructing abstract representations of domain dynamics.

Valmeekam et al. (2024) demonstrate that this semantic obfuscation creates a striking performance gap between model types. Instruction-tuned large language models drop to near-zero accuracy on Mystery BlocksWorld. In contrast, reasoning models – a new class of models trained via reinforcement learning to generate extended chains of thought (Xu et al., 2025) – maintain 20-30% accuracy even under complete semantic obfuscation. These reasoning models, including OpenAI's o1 (OpenAI, 2024), DeepSeek R1 (DeepSeek-AI, 2025), and QwQ-32B (Qwen Team, 2025), produce long step-by-step reasoning traces that often span tens of thousands of tokens. Their ability to maintain performance under semantic obfuscation suggests they are doing something fundamentally different: dynamically constructing abstract problem representations during reasoning itself, rather than relying on memorized semantic associations.

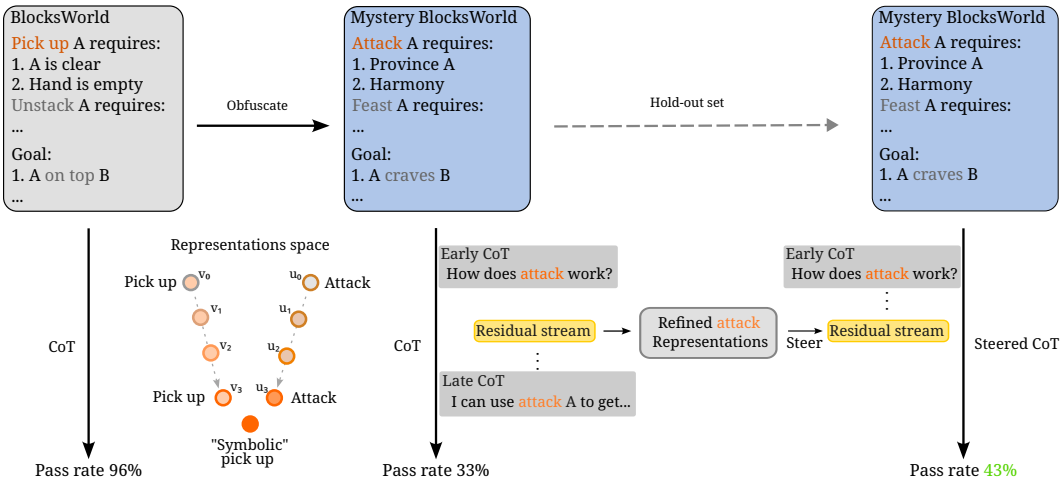


Figure 1: **Overview of our pipeline.** Left: QwQ-32B's accuracy on Standard BlocksWorld is 96%. Center: Mystery BlocksWorld obfuscates semantics (e.g., "pick up" → "attack"), reducing QwQ's accuracy to 33%. During extended reasoning traces, the model progressively refines internal representations of obfuscated actions, developing abstract symbolic encodings (vectors $v_0, \ldots, v_3$, and $u_0, \ldots, u_3$ are extracted at different Chain-of-Thought timestamps). Right: Steering experiments inject these refined representations into early reasoning stages, improving accuracy up to 43%, demonstrating that representational adaptations causally contribute to problem-solving performance.

Despite the growing interest in understanding these capabilities, mechanistic insights into how extended reasoning traces benefit model performance remain limited. A major section of reasoning interpretability research focuses on identifying universal reasoning circuits through common token or representation-level components (Venhoff et al., 2025; Bogdan et al., 2025; Lee et al., 2025; Galichin et al., 2025). However, another possible approach is to examine the problem representations that these circuits operate on. An example of this approach is a recent work on state tracking in toy reasoning models (Zhang et al., 2025)

We take this representational approach to investigate how reasoning models develop "understanding" of the abstract problem structure during their reasoning. Prior work shows that models adapt internal representations when words acquire new meanings in toy in-context learning setups (Park et al., 2025). We extend their methodology to reasoning traces in planning tasks and establish causal relevance through extensive steering experiments that test whether learned representations actually contribute to problem-solving performance.

We focus our analysis on QwQ-32B (Qwen Team, 2025), the most capable open-source reasoning model available, and examine its internal representations while solving Mystery BlocksWorld (Valmeekam et al., 2023) puzzles. Our central hypothesis is that reasoning models progressively refine their internal representations of problem entities during reasoning, developing context-specific semantics that enable abstract structural reasoning independent of surface-level semantics.

Key Observations. Our main findings about the internal mechanisms of reasoning models are:

1. **Representational Dynamics** (Section 3): We observe that QwQ-32B progressively adapts internal representations of actions and predicates during reasoning, with these adaptations converging toward consistent encodings regardless of initial action names.
2. **Causal Validation** (Section 4): Through steering experiments, we observe that these representational adaptations causally improve problem-solving performance. Injecting refined representations from successful reasoning traces into early stages of reasoning enhances accuracy on held-out puzzles, with averaged cross-naming representations achieving the strongest effects.
3. **Symbolic Abstraction** (Sections 3.2 and 4.2): We observe that adapted representations achieve symbolic abstraction, enabling cross-naming transfer. Models can operate effectively when naming-specific representations are replaced with averaged symbolic representations, suggesting convergence toward abstract structural encodings.

Our findings suggest that the superior performance of reasoning models on abstract reasoning tasks stems, at least partially, from their ability to dynamically construct problem-specific representational spaces during reasoning. This capability represents a fundamental advance in how language models process and represent abstract structural information, with implications for understanding and improving reasoning capabilities in future system.

2 Background

BlocksWorld. BlocksWorld is a classic planning domain from the International Planning Competitions (IPC, 1998). Each puzzle specifies initial and goal block arrangements, with constraints that agents can hold only one block at a time and cannot pick up blocks with others stacked above them. The domain defines four core **actions**: *pick-up*, *put-down*, *stack*, and *unstack*. The state is described using **predicates** such as *on(x,y)* (block x is on block y) or *on-table(x)* (block x is on the table). Full prompt can be found in A. We use PlanBench (Valmeekam et al., 2023) for problem generation and verification. Despite conceptual simplicity, base models fail to achieve perfect accuracy on four-block problems, while reasoning models demonstrate substantially superior performance (Valmeekam et al., 2024).

Mystery BlocksWorld. Mystery BlocksWorld (Valmeekam et al., 2023) replaces all predicates and actions with semantically unrelated words through alternative **namings** – systematic remappings where, for example, the action *pick-up* becomes *attack* and the predicate *on(x, y)* becomes *craves(x, y)* (prompt example in Appendix B). Each naming provides a complete semantic obfuscation that preserves the underlying logical structure while causing dramatic performance degradation. Success requires models to operate on abstract structural relationships and dynamically construct new semantic mappings from these obfuscated terms – capabilities reasoning models demonstrate significantly better than base LLMs.

We generated **14 additional naming variants** beyond the original, creating 15 different semantic obfuscations of the same domain structure (see Appendix F). We selected this domain because its fixed action space and strict rules provide a clear concept set for both the model and our analysis.

Terminology. We refer to each unique initial-goal state combination as a **puzzle** and each mapping variant as a **naming**. Our analysis focuses on 300 four-block puzzles, each mapped across all 15 mystery namings.

2.1 Initial Evaluations

We conducted evaluations of various models on our BlocksWorld puzzle dataset to establish baseline performance and validate our choice of QwQ-32B for detailed analysis. They are available in Table 1.

Reasoning models consistently outperform standard LLMs on both regular and Mystery BlocksWorld tasks, though open-source reasoning models of moderate size remain limited, with DeepSeek distillation models showing particularly poor Mystery BlocksWorld performance. QwQ-32B demonstrates exceptional performance on both variants, with successful Mystery BlocksWorld solutions typically requiring 15-20k token reasoning traces – substantially longer than regular BlocksWorld problems and crucial for the semantic adaptation process investigated in this work. While Nemotron generates similarly long reasoning traces, QwQ-32B achieves superior accuracy across most mystery namings

we have generated. We also provide reasoning behavior breakdown similar to Venhoff et al. (2025) in Appendix C.

Table 1: Performance comparison of models on BlocksWorld and **Naming 1** Mystery BlocksWorld puzzles (all 300). "Accuracy Preserved" indicates the percentage of accuracy retained. "Tokens" represents the average length of the CoT. **Llama Nemotron computes the correct answer more often, but often answers with incorrect formatting which the evaluation suite cannot parse.*

Model	**BlocksWorld**		**Mystery**		**Accuracy Preserved**
	`Acc`	`Tokens`	`Acc`	`Tokens`	
Regular LLMs					
GPT-4.1 (CoT)	0.92	556	0.18	3837	**20%**
Qwen2.5-32B	0.21	71	0.00	1390	**0%**
Qwen2.5-32B-Instruct (CoT)	0.38	353	0.00	1479	**0%**
Llama 3.3 70B Instruct (CoT)	0.40	760	0.02	1142	**5%**
Reasoning Models					
DeepSeek-R1-Distill-Qwen-32B	0.81	2387	0.08	8500	**10%**
DeepSeek-R1-Distill-Llama-70B	0.66	2674	0.10	10636	**15%**
Llama Nemotron Super 49B v1	0.48*	1162	0.19	9200	**40%**
QwQ-32B	0.96	3633	0.35	16186	**36%**

2.2 Mystery Performance Analysis

QwQ-32B's accuracy varies *dramatically* across mystery namings, from 0.05 to 0.47. The model performs worst on namings suggesting reversible operations ("open/close," "plant/harvest") or coherent alternative domains (legal proceedings, gardening cycles), while abstract philosophical terms, mixed sensory modalities, and semantically incoherent combinations enable better performance. This suggests that *semantically connected actions and predicates make it much harder for the model to abstract away* from their initial meanings. To verify this hypothesis, we generated several additional naming variants beyond the original 15, though these are not included in most experiments (see Appendix G for all results). Our steering experiments on the early layers (4.1 also suggest a connection between the semantics of the replacement words and the final performance.

As a special case, *Mystery naming 3* uses random strings, causing the model to explicitly recognize the task as BlocksWorld and directly map obfuscated terms to actions, as evidenced by substantially shorter reasoning traces (2k vs 15-20k tokens) and manual trace analysis. This suggests that some version of Mystery BlocksWorld was present in QwQ-32B's training data. Since we do not observe the model recognizing the BlocksWorld domain in reasoning traces for other namings, we believe it genuinely attempts to discover solutions rather than retrieving them from memory in those cases. We exclude naming 3 from representational analyses as it bypasses the semantic adaptation process under investigation.

2.3 Representation Collection

Overview. Our goal is to extract vector representations of actions and predicates from the model's internal activations as it reasons about BlocksWorld puzzles. We build on the methodology of Park et al. (2025), applying it to reasoning traces collected from BlocksWorld and Mystery BlocksWorld puzzles from our dataset.

Representation extraction. Given a batch $\mathcal{B}$ of reasoning traces, action (predicate) a, naming N, layer $L \in \{1, \ldots, L_{\max}\}$, and timestamp T (token position in the sequence), we extract the representation $\mathbf{r}_a^{N,L,T}$ as follows:

1. **Window extraction:** For each trace in $\mathcal{B}$, consider tokens in the window $[T - w, T)$ where w is the window size (we use $w = 100$).
2. **Token selection**. Find all token sequences that encode a. (For example ["att", "ack"] for "attack"). For each sequence also include one token before.

3. **Averaging:** Extract hidden states $\mathbf{h}_i^L$ at layer L for all matched token positions. Average within each matched sequence, then average across all sequences in the batch:

$$\mathbf{r}_a^{N,L,T} = \frac{1}{|\mathcal{S}|} \sum_{s \in \mathcal{S}} \left(\frac{1}{|s|} \sum_{i \in s} \mathbf{h}_i^L \right) \tag{1}$$

where $\mathcal{S}$ is the set of all matched sequences across the batch, and s denotes the token positions in a matched sequence.

We repeat this process across multiple timestamps (every 200 tokens) and all layers to obtain a comprehensive set of representations for each action (predicate).

In-naming representations. For each mystery naming N, we collect **in-naming representations** $\mathbf{r}_a^{N,L,T}$ for each action (predicate) a at all layers L and multiple timestamps T. To isolate the action direction within a naming, we create *centered* representations Venhoff et al. (2025):

$$\tilde{\mathbf{r}}_a^{N,L,T} = \mathbf{r}_a^{N,L,T} - \frac{1}{|\mathcal{A}|} \sum_{a' \in \mathcal{A}} \mathbf{r}_{a'}^{N,L,T} \tag{2}$$

where $\mathcal{A}$ is the set of all actions (or predicates) in the domain.

Cross-naming representations. To extract the abstract, symbolic meaning of an action (predicate) independent of its surface form, we compute **cross-naming representations** by averaging centered in-naming representations across all namings:

$$\bar{\mathbf{r}}_a^{L,T} = \frac{1}{|\mathcal{N}|} \sum_{N \in \mathcal{N}} \tilde{\mathbf{r}}_a^{N,L,T} \tag{3}$$

where $\mathcal{N}$ is the set of all namings. This averaging operation should cancel out naming-specific surface features and preserve only the invariant semantic core – the actual logical meaning of the concept in the Mystery BlocksWorld context.

3 Representational Studies

Our main hypothesis is that reasoning models progressively refine their internal representations of problem entities during extended reasoning. We call such refined representations Fluid Reasoning Representations, named after fluid reasoning in humans (Ferrer et al., 2009; Wu et al., 2025). This process develops context-specific semantics that enable abstract structural reasoning independent of surface-level word meanings. We test this hypothesis by analyzing how QwQ-32B's (Qwen Team, 2025) representations of actions and predicates evolve while solving Mystery BlocksWorld (Valmeekam et al., 2023) puzzles.

3.1 Cross-Naming Representational Convergence

If our hypothesis is correct, then semantically equivalent actions should converge to similar internal encodings across different mystery namings, regardless of their surface-level differences.

As a first step to investigate our hypothesis, we extract **in-naming** representations from Mystery naming 1 at timestamps 2k, 4k, 7k, and 10k tokens, then compute cosine similarities between these and centered representations from all timesteps across all other mystery namings, averaging the results. On Figure 2, we plot two lines for each Mystery 1 timestamp: one for the average similarity of an action with corresponding action from other namings and another one for average similarities of the action with different actions from the other namings. The figure shows that except for timestamp 2k cross-naming similarity increases substantially during reasoning, plateauing around 7,000 tokens — typically coinciding with the model switching from examining single actions to trying building chains out of them. (Appendix C).

We also observe that similarities with different actions are always lower than with the corresponding ones. Relatively high (≈ 0.2) similarity is caused by representations of "stack" and "unstack" being closer to each other, than to "pick up" and "put down".

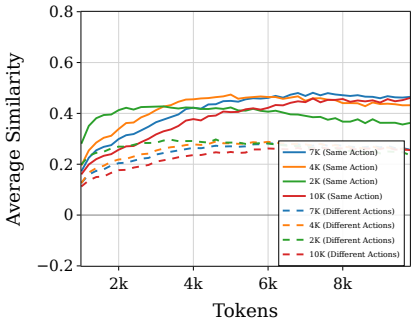


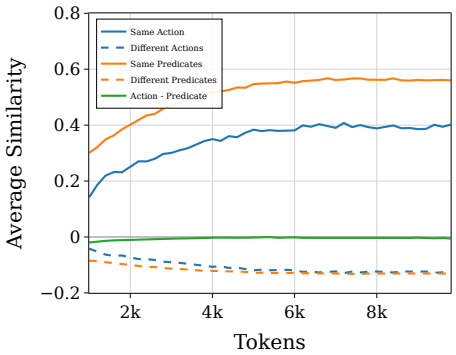
Figure 2: Average similarity of representations from other namings with naming 1 representations, extracted from different timestamps.

Figure 3: Layer-wise PCA of action representations from different mystery namings extracted at 7k tokens. More layers is Appendix D.

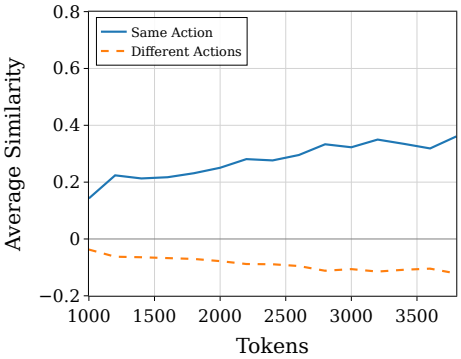
To visualize how representations cluster across namings, we perform PCA analysis on action representations extracted at 7k tokens from layers 10 and 40. Figure 3 demonstrates that semantically equivalent actions cluster together regardless of their surface-level naming, with clustering becoming apparent in deeper layers.

3.2 Similarity with Average and Original BlocksWorld

To better understand the nature of representational convergence, we examine similarities between naming-specific representations and average representations computed across all namings. This analysis reveals two important patterns that were obscured in the pairwise comparison.



(a) Similarities with average representations



(b) Similarities with clean BlocksWorld representations

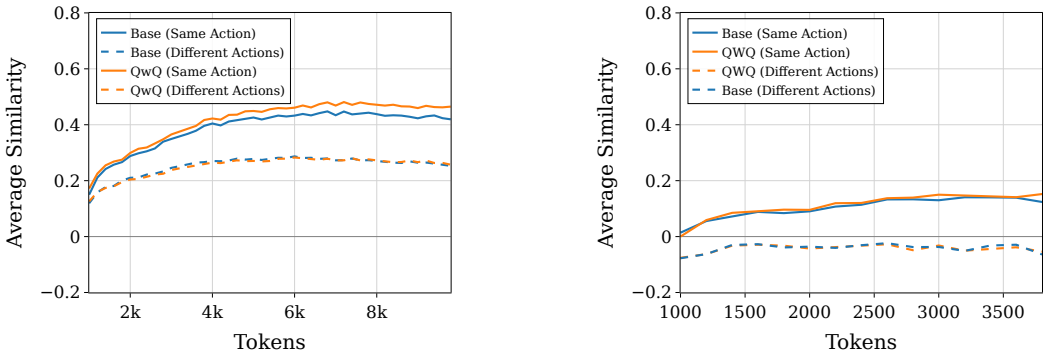
Figure 4: **Similarity with cross-naming representations between Mystery and Original BlocksWorld traces.** (a) Shows average similarities of centered action/predicate representations from all timestamps in Mystery Blocksworld traces with cross-naming representations extracted at 7k tokens. Note that similarities between different actions become increasingly negative. (b) Shows average similarities of clean BlocksWorld representations from all timestamps with cross-naming representations extracted at 7k tokens. Plot for predicates is absent, since it's much harder to identify their tokens in regular BlocksWorld traces.

First, when comparing centered representations with their corresponding average representations (Figure 4a), similarity increases substantially during reasoning, plateauing around 7,000 tokens. Crucially, similarities between different actions become increasingly negative as reasoning progresses. This shows the model actively differentiates between action types while developing shared encodings for equivalent actions across namings.

Second, we compare mystery naming representations at 7k tokens with clean BlocksWorld representations across all timestamps (Figure 4b). Similarity with clean BlocksWorld starts near zero

and increases substantially as clean reasoning progresses. This shows the model develops similar symbolic representations even with preserved semantic content, indicating that representational adaptation is a fundamental reasoning mechanism, not just compensation for semantic obfuscation.

3.3 Base Model Comparison



(a) Cross-naming similarity comparison

(b) Clean BlocksWorld similarity comparison

Figure 5: Average similarity of representations extracted from the 7k timestamp, plotted for both QwQ and its base model on QwQ traces. (a) Shows similarity of representations from other namings with naming 1 representations (averaged across all other namings). (b) Shows similarity of representations from original BlocksWorld traces with representations from different mystery namings (averaged across them).

We tested whether representational adaptation is specific to reasoning models by analyzing both QwQ and its base model processing identical QwQ-generated traces. Both models exhibit similar adaptation dynamics (Figure 5a), with the base model adapting slightly more slowly - likely due to processing unnatural traces. Both show comparable convergence toward shared symbolic representations (Figure 5b).

This finding, combined with prior work on in-context learning (Park et al., 2025), indicates representational adaptation is an inherent property of large language models rather than a specialized reasoning model feature. The difference is that reasoning models naturally produce the extended context needed to use these adaptations.

4 Causal validation

The representational analysis in Section 3 reveals that QwQ-32B dynamically adapts representations of actions and predicates beyond their original lexical meanings, with adaptations appearing independent of original word semantics.

This suggests two testable hypotheses: **(1)** representational adaptations reflect genuine improvements in understanding abstract puzzle structure, and **(2)** adapted representations achieve symbolic abstraction that transcends original tokens, enabling transfer across naming schemes. We design steering experiments to test whether learned representations contain actionable structural knowledge and can function independently of their linguistic context.

4.1 Positive Steering

To test hypothesis **(1)** – that representational adaptations reflect genuine improvements in understanding of abstract puzzle structure – we conduct positive steering experiments. We inject action and predicate representations extracted from late stages of reasoning traces into early reasoning traces and measure accuracy improvements. We find that these representations boost accuracy, demonstrating they encode operationally useful structural understanding. Furthermore, cross-naming representations improve performance across different namings, providing evidence for hypothesis **(2)**: symbolic abstraction that transcends specific lexical forms.

Experimental Setup. Our steering procedure selects a steering layer L, token window $[t_{\text{start}}, t_{\text{end}})$, and steering scale s. We collect three types of steering vectors at layer L from the 40 correctly solved puzzles: **(1)** centered **in-naming** representations $\tilde{\mathbf{r}}_a^{N,L,T}$ for all actions and predicates, **(2)** **cross-naming** representations $\bar{\mathbf{r}}_a^{L,T}$ averaged across all namings, and **(3)** random Gaussian vectors $\mathbf{v}_{\text{rand}}[a]$ scaled to match the norm of **in-naming** representations. We extract prefixes of t_{end} tokens from a hold-out set of 100 different 4-block problem rollouts as our intervention dataset.

For each prefix, we identify token indices i corresponding to action or predicate a, obtain hidden states $\mathbf{h}_i^L$ at layer L, and apply the following norm-preserving intervention:

$$\mathbf{h'}_i^L = s \cdot \mathbf{h}_i^L + (1 - s) \cdot \mathbf{v}_{\text{type}}[a], \tag{4}$$

$$\mathbf{h}_i^L \leftarrow \mathbf{h'}_i^L \cdot \frac{\|\mathbf{h}_i^L\|_2}{\|\mathbf{h'}_i^L\|_2}, \tag{5}$$

where $\mathbf{v}_{\text{type}}[a] \in \{\tilde{\mathbf{r}}_a^{N,L,T}, \bar{\mathbf{r}}_a^{L,T}, \mathbf{v}_{\text{rand}}[a]\}$ depending on the experiment condition. This procedure adds the refined representation while preserving activation magnitude. We measure accuracy improvement on steered puzzles compared to non-steered baseline. We selected scale $s = \frac{2}{3}$ after a sweep on layer 20 using **in-naming** representations (Appendix H.2). The steering window is $[1500, 2500]$.

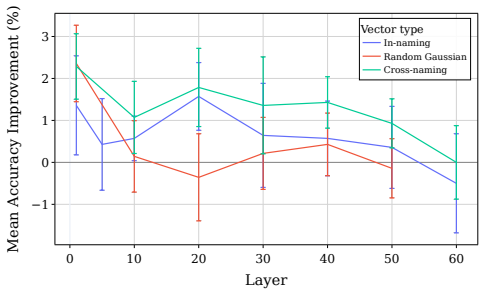


Figure 6: Accuracy improvement after positive steering averaged across mystery namings (excluding Naming 3). **Takeaways:** (i) Even random early-layer interventions ($L \leq 10$) already improve accuracy, suggesting they help remove surface-level naming associations. (ii) From $L \geq 20$ onward, steering with refined representations is most beneficial: *cross-naming* > *in-naming* ≫ random. Error bars show s.e. across namings. See Sec. 4.1.

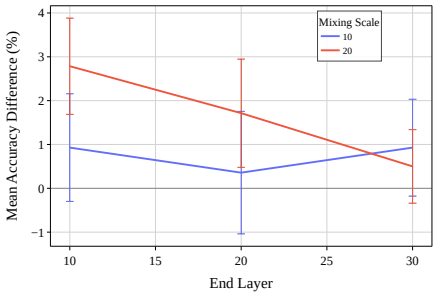


Figure 7: Mean accuracy difference between symbolic patching and shuffled control across scaling factors s. **Takeaways:** Matched *symbolic* representations outperform the shuffled baseline. This supports the *symbolic abstraction* hypothesis: the model can operate when naming-specific activations are replaced by naming-agnostic symbolic vectors. Error bars show s.e. across namings. See Section 4.2.

Results. Figure 6 shows accuracy improvements after positive steering, averaged across namings (excluding naming 3). Even random noise improves accuracy on early layers, suggesting that in this case disrupting original semantic associations helps overcome interference from misleading word meanings, which is consistent with our initial evaluations (Section 2.2).

Steering with **in-naming** representations improve performance with a notable drop before layer 20, where PCA analysis reveals the onset of action representation separation (Appendix D). This suggests accuracy improvements from layer 20 onward stem from representations becoming genuinely meaningful rather than noise effects. As a side note, we attempted to steer the **base model** using traces from the reasoning model, but did not achieve noticeable improvement, as the base model could not operate effectively with such long contexts without breaking down.

Cross-naming representations achieve the highest impact across all layers, reinforcing that these adaptations encode abstract problem structure rather than naming-specific artifacts. Together, these results support our hypothesis that learned adaptations contain meaningful structural understanding.

We also note a significant layer dependence for steering efficiency with different namings. This, along with some namings being much less responsive to steering, may be one of the reasons why average accuracy boost is relatively low (compared to gains of up to **10%** in some cases (Appendix G)).

4.2 Symbolic Patching

To test hypothesis **(2)** – that adapted representations achieve symbolic abstraction independent of surface forms – we conduct a patching experiment that replaces naming-specific representations with cross-naming "symbolic" representations and tests whether the model can operate effectively without access to the original naming-specific encodings.

Symbolic Representation Construction. We construct symbolic representations to be minimally out-of-distribution while capturing abstract structural information. We collect centered **cross-naming** representations $\bar{\mathbf{r}}_a^{L,T}$ for each action and predicate, compute the overall mean $\bar{\mathbf{r}}_{\text{mean}}^{L,T}$ across all actions (and separately for predicates), and construct symbolic representations as:

$$\mathbf{r}_{\text{symbolic}}[a] = \bar{\mathbf{r}}_{\text{mean}}^{L,T} + s \cdot \bar{\mathbf{r}}_a^{L,T} \tag{6}$$

where s is a mixing scale and $\bar{\mathbf{r}}_a^{L,T}$ is the centered cross-naming representation of action a.

Experimental Design. Since the model maintained reasonable accuracy even when all actions were replaced with a single vector, we use a comparative approach: **(1)** Symbolic Patching replaces residual stream activations for action/predicate tokens with corresponding symbolic representations, and **(2)** Shuffled Patching uses randomly permuted symbolic representations as control.

We patch token window [2000, 4000] on all layers until the selected end layer, then measure accuracy difference $\text{Acc}_{\text{symbolic}} - \text{Acc}_{\text{shuffled}}$. Figure 7 confirms that properly matched symbolic representations consistently outperform shuffled ones across scaling factors, supporting meaningful symbolic abstraction.

4.3 Negative Steering

To further test hypothesis **(1)**, we conduct negative steering by subtracting converged in-naming representations from model activations, aiming to disable the representational adaptations. Since steering interventions can easily degrade performance, we use shuffled representations as a comparative baseline. Performance degradation beyond the shuffled control demonstrates the adaptations encode operationally important structural understanding rather than arbitrary activation patterns.

Experimental Design. We perform interventions across token window [2000, 4000] on multiple layers, subtracting centered naming representations extracted from the 4k timestamp (selected as these are near convergence while at our window's end, see Figure 2). We use shuffled representations as control, as random vectors provided insufficient baseline strength.

With optimal layer selection, negative steering shows 2.9% accuracy mean difference with control (full results in Appendix E). This reinforces that representational adaptations play a crucial role in problem-solving, as disrupting learned representations leads to measurably worse performance even when controlling for general intervention effects..

5 Related Work

Interpretability of Language Models' Representations. Recent mechanistic interpretability research has converged on identifying meaningful directions in model representation spaces. Studies have demonstrated that large language models encode diverse features as linear directions in their activation spaces, including truthfulness (Li et al., 2023; Azaria & Mitchell, 2023; Marks & Tegmark, 2024; Zou et al., 2025), sentiment (Tigges et al., 2024), sycophancy (Perez et al., 2023; Panickssery et al., 2024; Sharma et al., 2024), factual knowledge (Gurnee & Tegmark, 2024), and refusal behavior (Arditi et al., 2024). Complementing these supervised approaches, sparse autoencoders have emerged as powerful tools for discovering feature directions in an unsupervised manner, revealing interpretable features at scale (Bricken et al., 2023; Huben et al., 2024; Templeton et al., 2024). These findings support the linear representation hypothesis; i.e., that neural networks encode semantic concepts as linear directions in high-dimensional activation spaces (Mikolov et al., 2013; Bolukbasi et al., 2016; Elhage et al., 2021; Nanda et al., 2023; Park et al., 2024; Olah, 2024). Beyond concept-based representations, single directions may also contain complex functional and structural information, such as generalized task definitions from in-context learning examples (Todd et al., 2024; Hendel et al.,

2023), new meanings of words in in-context learning (Park et al., 2025), user-specified instructions (Stolfo et al., 2025), or even reasoning behavior itself (Zhao et al., 2025).

Reasoning Interpretability. A major part of reasoning interpretability research focuses on identifying universal reasoning circuits through common reasoning components. These can be key intermediate sentences or "thought anchors" (Bogdan et al., 2025), reasoning behaviors like uncertainty expression and backtracking (Gandhi et al., 2025; Venhoff et al., 2025), self-verification directions (Lee et al., 2025), reasoning-related sparse autoencoder features (Galichin et al., 2025). As an alternative representations-based approach, Zhang et al. (2025); Hou et al. (2023) study state tracking or contents of a reasoning tree in toy transformers, while Arefin et al. (2025) looks at representations during reasoning from a compression perspective. Dutta et al. (2024) investigates attention patterns and shifts of representations spaces during different reasoning behaviors representing a mix of both approaches. Finally, Ward et al. (2025) compares representations in reasoning and base models, finding that reasoning-finetuning repurposes directions already present in base model activations.

6 Limitations

We focus on a single reasoning model (QwQ-32B) and a single domain (BlocksWorld). While this does not cover the full diversity of reasoning tasks, BlocksWorld offers a particularly clean testbed: it has a small, well-defined set of actions and predicates, clear structural rules, and easily controlled obfuscations. This makes it possible to isolate representational adaptation in a way that would be difficult in domains with unconstrained concept spaces, such as open-ended mathematics or natural language reasoning. We expect these findings to generalize to other structured planning setups with fixed action spaces (e.g., Towers of Hanoi), though verifying this and testing whether the patterns extend to less constrained domains remains future work.

Our steering and patching intervention methods are deliberately simple, chosen to remain tractable on reasoning traces that often span 15–20k tokens. More targeted or fine-grained causal tools could sharpen the picture, but even our coarse interventions reveal measurable effects. Similarly, computational limits prevented extensive hyperparameter sweeps or decoding strategy comparisons, yet the observed representational trends were consistent across multiple obfuscations. We also note that shuffled-control experiments (Appendix I) reveal unexpected gains around later layers (notably layer 30), suggesting that some aspects of late-layer representational dynamics remain to be explained in future work.

7 Conclusion

This work analyzed how a reasoning-oriented language model (QwQ-32B) processes abstract structural information during extended reasoning. We presented three main observations. First, the model progressively refines internal representations of actions and predicates over long reasoning traces, converging toward abstract encodings that are less dependent on surface-level semantics. Second, steering experiments suggest that these representational adaptations are not merely descriptive but can causally influence problem-solving performance: injecting refined representations tends to increase accuracy, while disrupting them tends to decrease it. Third, we observed evidence of symbolic abstraction, where representations transfer across different obfuscated namings, suggesting a degree of naming-invariant structural encoding.

Taken together, these results suggest that the superior performance of reasoning models on abstract reasoning tasks may stem in part from their ability to dynamically construct context-specific representational spaces during extended reasoning. While preliminary, our findings highlight representational refinement as a promising direction for understanding the internal mechanisms of reasoning models and contribute to a growing body of work on the interpretability of long-form reasoning traces.

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A BlocksWorld prompt example

```
I am playing with a set of blocks where I need to arrange the blocks
    into stacks. Here are the actions I can do

Pick up a block
Unstack a block from on top of another block
Put down a block
Stack a block on top of another block

I have the following restrictions on my actions:
I can only pick up or unstack one block at a time.
I can only pick up or unstack a block if my hand is empty.
I can only pick up a block if the block is on the table and the block
    is clear.
A block is clear if the block has no other blocks on top of it and if
    the block is not picked up.
I can only unstack a block from on top of another block if the block I
     am unstacking was really on top of the other block.
I can only unstack a block from on top of another block if the block I
     am unstacking is clear.
Once I pick up or unstack a block, I am holding the block.
I can only put down a block that I am holding.
I can only stack a block on top of another block if I am holding the
    block being stacked.
I can only stack a block on top of another block if the block onto
    which I am stacking the block is clear.
Once I put down or stack a block, my hand becomes empty.
Once you stack a block on top of a second block, the second block is
    no longer clear.

Here is an example problem:

[STATEMENT]
As initial conditions I have that, Block B is clear, Block C is clear,
     the hand is empty, Block C is on top of Block A, Block A is on
    the table, Block B is on the table.
My goal is to have that Block A is on top of Block C and Block B is on
     top of Block A

My plan is as follows:

[PLAN]
unstack Block C from on top of Block A
put down Block C
pick up Block A
stack Block A on top of Block C
pick up Block B
stack Block B on top of Block A
[PLAN END]
```

B Mystery prompt example

```
I am playing with a set of objects. Here are the actions I can do:
   Attack object
   Feast object from another object
   Succumb object
   Overcome object from another object

I have the following restrictions on my actions:
    To perform Attack action, the following facts need to be true:
        Province object, Planet object, Harmony.
```

```
    Once Attack action is performed the following facts will be true:
        Pain object.
    Once Attack action is performed the following facts will be false:
         Province object, Planet object, Harmony.
    To perform Succumb action, the following facts need to be true:
        Pain object.
    Once Succumb action is performed the following facts will be true:
         Province object, Planet object, Harmony.
    Once Succumb action is performed the following facts will be false
        : Pain object.
    To perform Overcome action, the following needs to be true:
        Province other object, Pain object.
    Once Overcome action is performed the following will be true:
        Harmony, Province object, Object Craves other object.
    Once Overcome action is performed the following will be false:
        Province other object, Pain object.
    To perform Feast action, the following needs to be true: Object
        Craves other object, Province object, Harmony.
    Once Feast action is performed the following will be true: Pain
        object, Province other object.
    Once Feast action is performed the following will be false:,
        Object Craves other object, Province object, Harmony.

Here is an example problem:
[STATEMENT]
As initial conditions I have that, province Block B, province Block C,
     harmony, Block C craves Block A, planet Block A, planet Block B.
My goal is to have that Block A craves Block C and Block B craves
    Block A.
My plan is as follows:
[PLAN]
feast Block C from Block A
succumb Block C
attack Block A
overcome Block A from Block C
attack Block B
overcome Block B from Block A
[PLAN END]
```

C Behavior analysis

Through manual investigation of DeepSeek and QwQ reasoning traces, we identified recurring behavioral patterns in Mystery BlocksWorld solving. Models begin with **comparative analysis**, examining initial and goal states to identify conflicting predicates. They then alternate between **recursive search** (working backwards from goals to identify required actions) and **exploration** (experimenting with actions to discover achievable states). These exploratory behaviors occupy the first half of reasoning traces. The second phase involves **plan formulation**, where models construct action sequences and verify validity, iteratively rebuilding when conflicts arise. The final phase consists of **plan verification**, where models validate solutions before committing to answers.

D Layer-wise PCA

Figure 8 shows how action representations cluster across different transformer layers. The clustering patterns become more pronounced in deeper layers, with clear separation between action types emerging around layers 20-30.

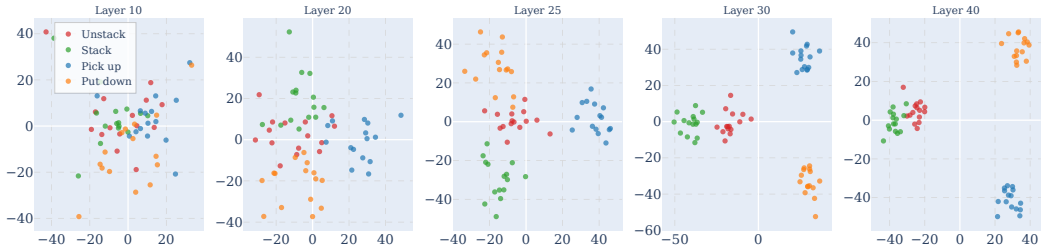

Figure 8: Layer-wise PCA of action representations from different mystery namings extracted at 7k tokens.

E Negative steering

To further validate the Structural Understanding Hypothesis, we conduct an ablation experiment testing whether disrupting representational adaptations decreases accuracy. Since steering interventions can easily degrade performance through general disruption rather than targeted ablation, we use a comparative approach.

We perform interventions across token window [2000, 4000] on multiple layers, subtracting centered naming representations extracted from the 4k timestamp. We use shuffled representations as control, as random vectors provided insufficient baseline strength. We start steering on layer 10 and perform two runs: 1) End layer 20 gives 2.3%$\pm$0.99% difference with random. 2) End layer 30 gives 2.9%$\pm$1.06%.

F Mystery BlocksWorld Naming Variants

Table 2: Action Mappings Across Mystery Namings

Naming	pick up	put down	stack	unstack
Mystery 1	attack	succumb	overcome	feast
Mystery 2	illuminate	silence	distill	divest
Mystery 3	tltezi	jchntg	deesdu	xavirm
Mystery 4	swim	fire	deduct	respond
Mystery 5	whisper	calculate	orbit	navigate
Mystery 6	decode	hibernate	thunder	quench
Mystery 7	explore	ripen	weave	bloom
Mystery 8	harvest	ignite	carve	suspend
Mystery 9	construct	demolish	reinforce	collapse
Mystery 10	plant	harvest	nurture	prune
Mystery 11	prosecute	acquit	testify	appeal
Mystery 12	broadcast	receive	encrypt	decode
Mystery 13	whisper	banish	entangle	unmask
Mystery 14	question	resolve	interweave	liberate
Mystery 15	summon	dismiss	fold	unravel
Additional Naming Variants				
Mystery 16	open	close	connect	disconnect
Mystery 17	chop	serve	season	taste
Mystery 18	release	grasp	separate	combine
Mystery 19	transcend	sublimate	actualize	deconstruct
Mystery 20	flixate	grample	chonder	sprill

Table 3: Predicate Mappings Across Mystery Namings

Naming	ontable	clear	handempty	holding	on
Mystery 1	planet	province	harmony	craves	pain
Mystery 2	aura	essence	nexus	harmonizes	pulse
Mystery 3	oxtslo	adohre	jqlyol	gszswg	ivbmyg
Mystery 4	fever	marble	craving	mines	shadow
Mystery 5	crystal	fountain	autumn	illuminates	legend
Mystery 6	prism	hollow	zenith	echoes	emblem
Mystery 7	fossil	dialect	equinox	fractures	symphony
Mystery 8	nebula	labyrinth	mirage	captivates	cascade
Mystery 9	eclipse	vintage	paradox	resonates	twilight
Mystery 10	crystal	puzzle	vortex	whispers	cipher
Mystery 11	nebula	molecule	anthem	silhouettes	voltage
Mystery 12	horizon	compass	solstice	orbits	quantum
Mystery 13	tethered	unburdened	hollow	shrouds	consuming
Mystery 14	echoing	sovereign	potential	obscures	contemplating
Mystery 15	suspended	timeless	interval	transcends	enveloping
Additional Naming Variants					
Mystery 16	paired	single	balanced	matches	mirrors
Mystery 17	plated	fresh	kitchen	simmering	marinated
Mystery 18	floating	occupied	crowded	repels	avoids
Mystery 19	phenomenal	unmediated	dialectical	instantiates	necessitates
Mystery 20	morkled	thristy	plimmish	vexates	quorbles

G Mystery Performance Analysis

Table 4: Performance across Mystery BlocksWorld naming variants with steering improvements. Columns with accuracy improvements display the maximum increase on layers 20, 30, 40 and 50.

Naming Variant	Base Acc.	In-Naming Steering	Cross-Naming Steering	Semantic Description
Mystery 1	0.33	+0.10	+0.11	Mixed violent/consumption metaphors
Mystery 2	0.47	+0.05	+0.05	Abstract mystical/spiritual terms
Mystery 3	0.65	—	—	Random strings
Mystery 4	0.25	+0.03	+0.03	Mixed physical actions
Mystery 5	0.24	-0.01	+0.01	Communication/navigation metaphors
Mystery 6	0.26	+0.05	+0.07	Technical/elemental operations
Mystery 7	0.19	+0.02	+0.03	Nature/growth cycle
Mystery 8	0.11	+0.02	+0.04	Agriculture/crafting metaphors
Mystery 9	0.25	+0.02	+0.01	Construction/destruction cycle
Mystery 10	0.05	+0.09	+0.05	Coherent gardening domain
Mystery 11	0.14	+0.00	+0.02	Legal proceedings domain
Mystery 12	0.16	+0.06	+0.02	Communication technology
Mystery 13	0.48	+0.06	+0.06	Dark mystical operations
Mystery 14	0.24	+0.02	+0.02	Abstract philosophical inquiry
Mystery 15	0.34	+0.04	+0.04	Mystical summoning/manipulation
Additional Variants				
Mystery 16	0.05	—	—	Reversible operations (open/close)
Mystery 17	0.27	—	—	Coherent cooking domain
Mystery 18	0.07	—	—	Physical manipulation verbs
Mystery 19	0.33	—	—	Abstract philosophical concepts
Mystery 20	0.29	—	—	Complete nonsense words

Table 4 reveals several patterns supporting our hypothesis that semantic coherence impedes abstraction. Namings with coherent alternative domains (Mystery 10: gardening, Mystery 11: legal proceedings, Mystery 16: reversible operations) achieve the lowest base accuracies, while abstract or semantically incoherent combinations (Mystery 2, Mystery 13) enable superior performance.

The steering improvement data shows notable heterogeneity across namings. The maximum improvements reported here represent the best performance across layers 20, 30, 40, and 50, as different namings exhibit optimal responsiveness at different depths. Some namings (Mystery 5, Mystery 11)

show minimal or no improvement from naming-mean steering, while others (Mystery 1, Mystery 10) demonstrate substantial gains. This suggests that certain semantic structures are more amenable to representational refinement than others.

H Implementation details

H.1 Steering engine

We implement steering using PyTorch forward hooks on top of vLLM v0.7.3 v0 Kwon et al. (2023), which provides substantial performance improvements, reducing experiment runtimes from several hours to tens of minutes compared to alternatives like TransformerLens (Nanda & Bloom, 2022) or NNSight Fiotto-Kaufman et al. (2024). However, this approach has tradeoffs: we must be mindful of cache recomputations, since they recompute representations without steering interventions, and vLLM's optimizations introduce some numerical instability during extended reasoning traces. To address this instability, we run experiments across multiple naming variants. All experiments use greedy decoding with maximum sequence length of 24,576 tokens.

H.2 Hyperparamters

We perform positive steering as described in Section 4.1 on layer 20 using **naming-mean** representations to determine the optimal steering scale. Figure 9 shows that scales $\frac{2}{3}$ and $\frac{4}{5}$ have similar effects. While improvement from $\frac{4}{5}$ is slightly higher, we chose $\frac{2}{3}$ since it has a more stable effect on all namings.

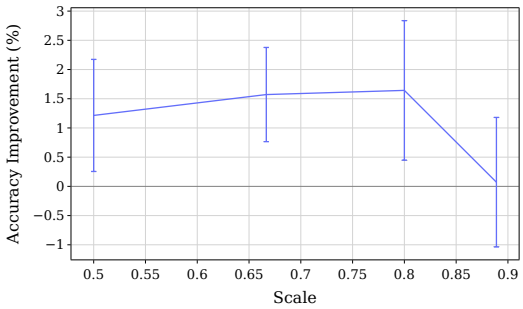

Figure 9: Positive steering results for layer 20 using different scale parameters s.

I Shuffled In-Naming Steering (Exploratory)

Setup. In addition to positive steering (Section 4.1), we tested a *shuffled in-naming* control. For each naming, we applied a single consistent permutation of centered in-naming vectors across actions/predicates (e.g., `pick up`→`stack`, `stack`→`put down`, etc.). This preserves per-naming distributional statistics while breaking the action–representation alignment. Interventions used the same window $[1500, 2500]$, scale $s = \frac{2}{3}$, and norm-preserving update rule as before, run on a reduced subset of layers and namings.

Findings. Figure 10 shows a three-phase trend: (i) early layers (≤ 5) improve relative to baseline, consistent with disruption of surface semantics; (ii) middle layers ($\sim 5 - 20$) degrade performance, likely breaking emerging abstractions; (iii) later layers ($\geq$30) again show improvements, comparable to unshuffled *in-naming*.

Interpretation. Early/mid results align with our story: disruption helps initially, but permutations harm once action-specific representations form. Late-layer gains suggest action vectors contain shared structural components, so even mismatched but in-manifold vectors can occasionally assist.

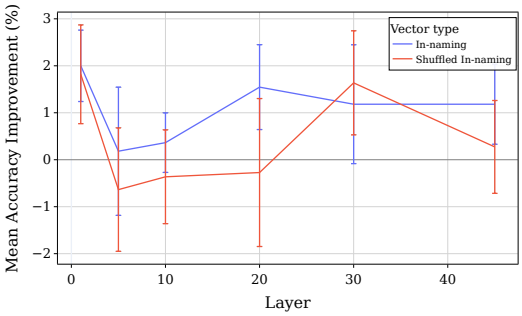

Figure 10: **Accuracy change under shuffled in-naming steering.** See Appendix I.

Caveat. These runs covered fewer namings/layers and late-layer effects were heterogeneous. We report them here for transparency; a fuller sweep is left to future work.