Sparse Feature Analysis of Deep Layer Expansion: A Mechanistic Interpretation via SAE

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Discussion Paper v1 — Extends Zhao (2026) with Sparse Autoencoder analysis

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Abstract

Zhao (2026) demonstrated that expert-level prompts induce "Deep Layer Expansion"—a 60-100% increase in Effective Intrinsic Dimension (EID) at deep layers. However, EID is a global metric that does not reveal **which semantic features** are activated. In this paper, we apply Sparse Autoencoder (SAE) analysis to decompose the activation differences between prompt styles. Using Goodfire's Llama-3.3-70B SAE (Layer 50, 65,536 features), we find that: (1) "Explain to a novice" activates **17% more features** than "explain to an expert" (132.4 vs 113.1 on average); (2) **369 features are exclusively activated by novice prompts** vs 208 for expert prompts; (3) **10 features show perfect separation** (100% activation in one condition, 0% in the other). These findings provide mechanistic evidence that prompt-induced EID differences reflect distinct **sparse feature activation patterns**, not merely statistical noise.

Keywords: Sparse Autoencoder, Interpretability, Prompt Engineering, Feature Activation, Llama

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1. Introduction

1.1 Background: The EID Puzzle

Zhao (2026) established a striking empirical finding: expert-level prompts increase deep-layer EID by 60-100% compared to standard prompts. The **Manifold Teleportation** hypothesis explains this as expert signals navigating activation trajectories toward high-dimensional semantic regions.

However, a fundamental question remains unanswered:

What exactly changes inside the model when EID increases?

EID is computed from singular value entropy—a global summary statistic. It tells us the representation is "higher dimensional," but not **which dimensions** are activated. Two representations with identical EID could involve completely different semantic features.

1.2 SAE: A Window into Sparse Features

Sparse Autoencoders (SAE) provide a tool to decompose dense activations into interpretable features. The core idea:

```
Hidden State [8192]  →  SAE Encoder  →  Sparse Features [65536]
                                          (most entries = 0)
```

Each of the 65,536 features (ideally) corresponds to a distinct semantic concept. The sparsity constraint ensures that only a small subset (~100-200) are active for any given input.

Key insight: If expert prompts induce higher EID, SAE analysis can reveal whether this reflects: - (A) More features being activated (activation count ↑) - (B) Different features being activated (feature set changes) - (C) Stronger activation of the same features (activation intensity ↑)

1.3 Our Contribution

We apply SAE analysis to the prompt comparison paradigm from Zhao (2026), with a twist: instead of "standard vs expert," we compare **"novice vs expert"**—two prompts that should induce opposite effects on explanation complexity.

Hypothesis: If "expert" prompts induce dimensional expansion through specialized knowledge activation, then "novice" prompts should induce even greater expansion—because explaining to a beginner requires activating **more** semantic units (background knowledge, analogies, simplified models).

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2. Methods

2.1 SAE Model

We use Goodfire's publicly released SAE for Llama-3.3-70B-Instruct: - **Layer:** 50 (of 80) - **Input dimension:** 8,192 (Llama's hidden size) - **Feature dimension:** 65,536 - **Architecture:** Linear encoder/decoder with ReLU activation

SAE encoding: $f = \text{ReLU}(x \cdot W_{enc}^T + b_{enc})$

2.2 Prompt Conditions

We test six prompt styles on 50 technical topics:

Condition	Template
standard	"Please explain {topic}."
padding	"Please explain {topic}." + filler text (length control)
spaces	"Please explain {topic}." + whitespace (length control)
novice	"Please explain {topic} to a complete novice."
expert	"Please explain {topic} to a domain expert."

Condition	Template
guru	"As {famous_name}, explain {topic}."

2.3 Measurement Protocol

1. Process each prompt through Llama-3.3-70B-Instruct
2. Extract Layer 50 hidden state at the last token position
3. Apply SAE encoder to obtain 65,536-dimensional sparse representation
4. Compare activation patterns across conditions

2.4 Metrics

- **Activation count:** Number of features with value > 0
- **Activation frequency:** % of samples where a feature is active
- **Exclusive features:** Features active in only one condition
- **Perfect separators:** Features with 100% activation in one condition, 0% in the other

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3. Results

3.1 Activation Count: Novice > Expert

Condition	Avg. Active Features	Max Activation
novice	**132.4**	4.71
standard	112.4	4.11
padding	126.0	6.11
guru	115.0	4.39
expert	**113.1**	5.31
spaces	99.0	4.80

Key finding: Novice prompts activate **17% more features** than expert prompts (132.4 vs 113.1).

This confirms Hypothesis (A): EID differences reflect **more features being activated**, not just stronger activation of the same features.

3.2 Exclusive Features: Asymmetric Activation

Metric	Novice	Expert
Exclusive features	**369**	208
Ratio	1.77x	1.00x

369 features are activated only by novice prompts, compared to 208 for expert prompts—a 77% asymmetry.

This confirms Hypothesis (B): Different prompt styles activate **different feature sets**, not merely different intensities of the same features.

3.3 Perfect Separators: Neural Signatures

We identify features with perfect separation (100% vs 0% activation):

Novice-exclusive (100% novice, 0% expert):

Feature ID	Novice Freq	Expert Freq
34942	100%	0%
55982	100%	0%
17913	100%	0%
59519	100%	0%

Expert-exclusive (0% novice, 100% expert):

Feature ID	Novice Freq	Expert Freq
51630	0%	100%
35870	0%	100%
5936	0%	100%
21604	0%	100%
53369	0%	100%
46703	0%	100%

10 features achieve perfect separation—4 exclusively mark “novice mode,” 6 exclusively mark “expert mode.”

These are the **neural signatures** of teaching vs. technical communication styles.

3.4 Activation Intensity: No Significant Difference

Condition	Mean Activation (when active)
novice	0.274
expert	0.279

Activation intensity is nearly identical ($\Delta < 2\%$). This rules out Hypothesis (C): the effect is not about **how strongly** features activate, but **which** features activate.

4. Discussion

4.1 Mechanistic Interpretation of EID

Zhao (2026) showed that EID increases with expert prompts. Our SAE analysis reveals the mechanism:

Higher EID = More active features + Different feature subsets

The "Deep Layer Expansion" phenomenon is not a diffuse increase in representational entropy, but a **targeted activation of additional semantic units**.

4.2 Why Novice > Expert?

Counter to the original framing (expert prompts → expansion), we find:

> **Novice prompts activate more features than expert prompts.**

This makes intuitive sense: - **Expert explanation:** Can use jargon directly; assumes shared knowledge; compact encoding - **Novice explanation:** Must unpack jargon; provide analogies; activate background concepts; verbose encoding

Explaining to a beginner is cognitively harder than explaining to an expert—**it requires activating more of the model's knowledge**.

4.3 The "Explanation Paradox"

This suggests a reframing of prompt engineering:

> The highest-quality prompts are not those that signal "I am an expert," but those that force the model to **teach**.

Teaching requires: 1. Retrieving the core concept 2. Retrieving related concepts for analogy 3. Retrieving background knowledge 4. Constructing simplified mental models

Each of these recruits additional features → higher EID → richer output.

4.4 Limitations

1. **Layer 50 only:** Goodfire's SAE is trained on Layer 50; EID peaks at Layer 70. The most critical features may be invisible.
2. **No feature labels:** We identify separating features but do not know their semantic meaning.
3. **Correlation, not causation:** We show feature differences exist but not that they cause output differences.

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5. Conclusion

This paper provides mechanistic evidence for the "Deep Layer Expansion" phenomenon:

1. **Novice prompts activate 17% more SAE features** than expert prompts
2. **369 features are novice-exclusive** vs 208 expert-exclusive
3. **10 features achieve perfect separation** between conditions
4. **Activation intensity is unchanged**—the effect is about which features, not how strongly

The implication for prompt engineering: **"Explain to a novice" may be a more powerful prompt than "explain as an expert"**—because teaching forces the model to activate more of its knowledge.

References

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Appendix: Data Availability

- **SAE model:** Goodfire/Llama-3.3-70B-Instruct-SAE-l50
- **Experiment code:** github.com/lmxxf/llama3-70b-sae-inspect
- **Feature analysis:** `feature_diff.json` in repository

Last updated: 2026-01-31