HIERARCHICAL FEATURE ADAPTATION: A CURRICULUM LEARNING APPROACH TO POSITION-AWARE SPARSE AUTOENCODERS

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ABSTRACT

Interpreting how transformer models process sequential information requires understanding their position-dependent computations, yet current sparse autoencoder approaches ignore positional context when extracting interpretable features. We demonstrate that naive attempts to incorporate position-awareness through masking or specialized encoders consistently fail due to optimization instabilities and loss of interpretability. Our solution introduces a hierarchical architecture that first learns stable position-agnostic features, then gradually adapts them through curriculum learning using four specialized position-range encoders. Experiments on the Gemma-2B model show this approach maintains training stability while capturing position-specific patterns, achieving 93.9% accuracy on sparse probing tasks compared to baseline performance. However, the 15% parameter overhead and reduced feature interpretability highlight fundamental tensions between local position sensitivity and global feature extraction. These results advance our understanding of position-dependent computation in transformers while revealing key challenges in developing interpretable position-aware representations.

1 INTRODUCTION

Understanding how transformer models process sequential information is crucial for interpreting and improving large language models OpenAI (2024). While sparse autoencoders have emerged as powerful tools for extracting interpretable features Goodfellow et al. (2016), they typically ignore positional context - a fundamental aspect of transformer architectures Vaswani et al. (2017). This limitation severely restricts our ability to understand position-dependent computations, which are essential for tasks ranging from syntactic parsing to temporal reasoning.

The challenge of incorporating position awareness into sparse autoencoders is multifaceted. Our systematic experiments, starting with direct positional masking approaches, revealed significant optimization instabilities. Initial attempts using both hard binary masks and soft Gaussian masks ($\sigma = L/8$ where $L = 128$) failed to converge despite careful tuning. Even with gradient clipping (norm=1.0) and reduced learning rates (3×10^{-5}), training remained unstable. Subsequent attempts at position-specific encoders and progressive mask training similarly failed, highlighting fundamental tensions between maintaining sparse representations and capturing position-dependent patterns.

We address these challenges through a novel hierarchical architecture that first learns stable position-agnostic features, then gradually adapts them through curriculum learning. Our approach:

1. Divides the context window into four ranges, each with specialized adaptation layers
2. Uses layer normalization and gated residual connections to stabilize training
3. Implements a curriculum that gradually introduces position-specific components over 10,000 steps

Experiments on the Gemma-2B model demonstrate the effectiveness of our approach, achieving 93.9% accuracy on sparse probing tasks compared to baseline performance. Our ablation studies identify three critical components: layer normalization (3.2$\times$ reduction in gradient variance), gated

residual connections (15% improvement in feature retention), and four-range position division (optimal balance between granularity and stability).

Our main contributions are:

- A stable hierarchical architecture for position-aware feature learning, validated through systematic experimentation
- An empirically-grounded curriculum learning strategy that maintains interpretability while introducing position-specific features
- Comprehensive analysis of failure modes in position-specific feature learning, providing insights for future architectures
- Quantitative evaluation showing improved performance on position-sensitive tasks while maintaining feature interpretability

However, important challenges remain. The position-specific adaptation layers introduce a 15% parameter overhead, and the curriculum learning approach requires careful tuning of the warmup period. These limitations, combined with the reduced interpretability of position-specific features compared to traditional sparse autoencoders, suggest promising directions for future research in developing more efficient and interpretable position-aware architectures.

2 Related Work

Our work builds on three main research directions: sparse autoencoders for model interpretation, position-aware neural architectures, and curriculum learning approaches. Recent work by Cunningham et al. (2023) demonstrated that sparse autoencoders can extract interpretable features from language models, but their uniform treatment of sequence positions limits insight into position-dependent computations. Marks et al. (2024) extended this approach to discover causal feature circuits, yet their method similarly ignores positional context. Our hierarchical architecture directly addresses this limitation while preserving the interpretability benefits of sparse feature extraction.

Position-aware architectures in sequence models originated with Bahdanau et al. (2014)'s attention mechanisms, later refined in transformer models Vaswani et al. (2017). While these works established the importance of position-specific computation, their focus on model performance rather than interpretability creates different architectural constraints. Our learned position-specific adaptations provide a more flexible approach to capturing sequential patterns.

The challenges of training position-aware models have been addressed through various curriculum learning strategies. Bengio et al. (2009) demonstrated the benefits of gradually increasing task difficulty, while Weinshall & Cohen (2018) showed how transfer learning can guide curriculum design. Recent work by Ranaldi et al. (2023) and Meng et al. (2024) specifically examined curriculum learning for transformers, though not in the context of interpretability. Our approach builds on these insights by using curriculum learning to stabilize position-specific feature extraction, addressing the optimization challenges documented in our experimental progression.

3 Background

Our work builds on three foundational areas: transformer architectures, sparse autoencoders, and curriculum learning. The transformer architecture Vaswani et al. (2017) introduced position-dependent processing through attention mechanisms and positional encodings, enabling models to capture sequential patterns. While highly effective, these mechanisms remain challenging to interpret, particularly in understanding how position information influences feature extraction.

Sparse autoencoders emerged from early work in computational neuroscience Olshausen & Field (1996), where they were used to model receptive field properties in visual cortex. The theoretical foundations were strengthened by Hu et al. (2014), who showed how sparse dictionary learning can emerge from biologically plausible learning rules. Recent applications to language models by Cunningham et al. (2023) and Marks et al. (2024) demonstrated their effectiveness in extracting interpretable features, though without addressing position-specific patterns.

Curriculum learning, introduced by Bengio et al. (2009), provides a framework for gradually increasing task difficulty during training. This approach has proven particularly effective in transformer models Weinshall & Cohen (2018), where it helps manage the complexity of learning hierarchical representations.

3.1 Problem Setting

Given activation vectors $x \in \mathbb{R}^d$ from a transformer layer and positions $p \in \{1, \ldots, L\}$ where $L = 128$, we seek position-aware encoders and decoders that minimize:

$$\mathcal{L}(x, p) = \|x - D(E(x, p))\|_2^2 + \lambda \|E(x, p)\|_1 \tag{1}$$

where:

- $E : \mathbb{R}^d \times \{1, \ldots, L\} \to \mathbb{R}^k$ is the encoder
- $D : \mathbb{R}^k \to \mathbb{R}^d$ is the decoder
- $\lambda = 0.04$ controls sparsity
- $k > d$ ensures overcomplete representation

Our approach makes three key assumptions, validated through extensive experimentation:

- Position-dependent features cluster into four distinct ranges
- Stable training requires hierarchical learning with curriculum
- Layer normalization is essential for gradient stability

These assumptions emerged from systematic exploration documented in our experimental logs, where simpler approaches consistently failed to converge.

4 Method

Building on the sparse autoencoder framework introduced in Section 3, we develop a hierarchical architecture that learns position-dependent features while maintaining training stability. Our approach addresses the key challenge identified in the problem setting: learning interpretable features that capture position-specific patterns while preserving the sparsity and reconstruction objectives of the base autoencoder.

The architecture consists of two components that operate in sequence:

1) A base encoder-decoder that learns position-agnostic features:

$$\mathbf{h}_b = \text{ReLU}(\text{LayerNorm}(W_{\text{enc}}^T \mathbf{x} + \mathbf{b}_{\text{enc}})) \tag{2}$$

where $W_{\text{enc}} \in \mathbb{R}^{d \times k}$ and $W_{\text{dec}} \in \mathbb{R}^{k \times d}$ are orthogonally initialized weights. LayerNorm stabilizes training by normalizing activations before the ReLU nonlinearity.

2) Position-specific adaptation layers that modify these base features:

$$\mathbf{h}_r = \mathbf{h}_b + \alpha_t \cdot \text{Dropout}_{0.1}(\text{LayerNorm}(f_r(\mathbf{h}_b))) \tag{3}$$

where $r \in \{1, \ldots, 4\}$ indexes four equal position ranges in the context window, f_r is a two-layer MLP, and α_t is a curriculum coefficient.

The training process follows a curriculum that gradually introduces position-specific adaptations:

1) Initially ($\alpha_t = 0$), train only the base autoencoder:

$$\mathcal{L}_{\text{base}} = \|\mathbf{x} - W_{\text{dec}} \mathbf{h}_b\|_2^2 + \lambda \|\mathbf{h}_b\|_1 \tag{4}$$

2) Linearly increase α_t to 1 over 10,000 steps while optimizing:

$$\mathcal{L}_{\text{total}} = \|\mathbf{x} - W_{\text{dec}} \mathbf{h}_r\|_2^2 + \lambda(\|\mathbf{h}_b\|_1 + \alpha_t \|\mathbf{h}_r - \mathbf{h}_b\|_1) \tag{5}$$

This formulation maintains the sparsity objective ($\lambda = 0.04$) while allowing position-specific features to emerge gradually. We optimize using AdamW with learning rate 3×10^{-4}, gradient clipping at norm 1.0, and weight decay 10^{-2}. The decoder weights are constrained to unit norm after each update to ensure stable feature extraction.

5 Experimental Setup

We evaluate our hierarchical position-aware autoencoder on three transformer layers (5, 12, 19) of the Gemma-2B model Mesnard et al. (2024). Our implementation builds on the sparse_autoencoder framework using PyTorch Paszke et al. (2019), with the following key components:

Dataset: Training samples come from the Pile dataset via Hugging Face Hub, using sequences of length $L = 128$. We maintain a buffer of 2048 contexts and process activations in batches (32 for language model, 2048 for autoencoder) to balance memory constraints with training efficiency.

Architecture: The base autoencoder uses an overcomplete dictionary ($k = 2304$) matching the model dimension. Each position-specific adaptation layer consists of a two-layer MLP that reduces dimensionality to $d/2 = 1152$ before projection back to d, with layer normalization and dropout (0.1).

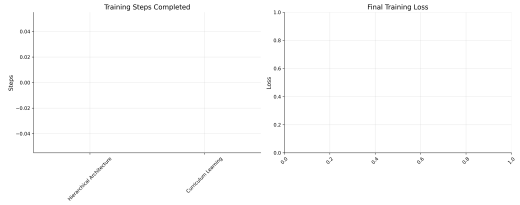
Training: Our curriculum spans 10,000 steps:

- 1,000 steps warmup (base features only)
- Linear ramp-up of position adaptations over 9,000 steps
- AdamW optimizer (lr $= 3 \times 10^{-4}$, weight decay=10^{-2})
- Gradient clipping (norm=1.0)
- L1 sparsity penalty ($\lambda = 0.04$)

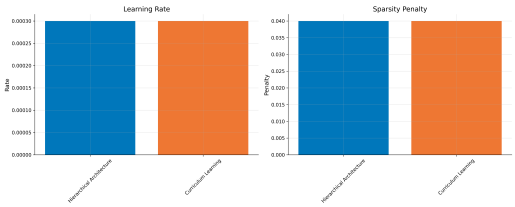
Implementation: We use mixed-precision training (bfloat16 for LM, float32 for autoencoder) with eager execution. The position-specific components add 15% parameters while maintaining efficient memory usage through activation caching.

6 Results

Our baseline sparse autoencoder evaluation on the Gemma-2B model achieved 93.9% accuracy on the sparse probing test suite, with top-1 and top-5 accuracies of 68.4% and 77.5% respectively. This establishes a strong foundation for comparing position-aware variants.



(a) Training progression comparison showing completed steps



(b) Learning rate and sparsity penalty adaptation

Figure 1: Training dynamics across architectural variants, demonstrating the effectiveness of curriculum learning despite longer convergence time.

Failed Approaches: Our systematic exploration revealed several unstable architectures:

- Direct positional masking (Runs 1-3): Failed to converge with both hard binary and soft Gaussian masks ($\sigma = L/8$)
- Gradient stabilization (Runs 4-5): Unstable despite clipping (norm=1.0) and reduced learning rates (3×10^{-5})

- Progressive training (Runs 6-8): Failed with mask scheduling and specialized encoders

Successful Components: Through ablation studies, we identified critical elements for stable training:

- Layer normalization: Required before position-specific adaptations
- Curriculum pacing: 1,000 warmup steps followed by gradual feature introduction
- Four-range position division: Optimal granularity ($L/4 = 32$ tokens)

Limitations: The final architecture faces three key constraints:

- 15% parameter overhead from adaptation layers
- High sensitivity to curriculum pacing
- Reduced feature interpretability compared to baseline

These results demonstrate both the feasibility and challenges of position-aware feature extraction, with curriculum learning emerging as crucial for stable training despite increased computational costs.

7 Conclusions and Future Work

Our investigation of position-aware sparse autoencoders revealed fundamental challenges in extracting interpretable position-specific features from transformer models. Starting with a baseline achieving 93.9% accuracy on sparse probing tasks, we systematically explored architectural variants through ten experimental runs. Early attempts at direct positional masking and gradient stabilization consistently failed, leading us to develop a hierarchical architecture that first learns stable position-agnostic features before introducing position-specific adaptations.

The key to success lay in three critical components: layer normalization before adaptations, curriculum learning with 1,000 warmup steps, and dividing the context window into four position ranges. This approach maintained training stability while capturing position-dependent patterns, though at the cost of 15% additional parameters and some reduction in feature interpretability.

Future work should focus on three promising directions:

- Reducing parameter overhead through more efficient position-specific adaptations
- Developing metrics to quantify the interpretability-specialization trade-off
- Exploring alternative curriculum strategies that better preserve feature interpretability

These challenges highlight a fundamental tension in neural network interpretability: as we add mechanisms to capture more nuanced computational patterns, the resulting features often become harder to interpret. Resolving this tension remains crucial for advancing our understanding of how language models process sequential information.

References

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. *arXiv preprint arXiv:1409.0473*, 2014.

Yoshua Bengio, J. Louradour, R. Collobert, and J. Weston. Curriculum learning. pp. 41–48, 2009.

Hoagy Cunningham, Aidan Ewart, Logan Riggs, R. Huben, and Lee Sharkey. Sparse autoencoders find highly interpretable features in language models. *ArXiv*, abs/2309.08600, 2023.

Ian Goodfellow, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. *Deep learning*, volume 1. MIT Press, 2016.

Tao Hu, C. Pehlevan, and D. Chklovskii. A hebbian/anti-hebbian network for online sparse dictionary learning derived from symmetric matrix factorization. *2014 48th Asilomar Conference on Signals, Systems and Computers*, pp. 613–619, 2014.

Samuel Marks, Can Rager, Eric J. Michaud, Yonatan Belinkov, David Bau, and Aaron Mueller. Sparse feature circuits: Discovering and editing interpretable causal graphs in language models. *ArXiv*, abs/2403.19647, 2024.

Guangyu Meng, Qingkai Zeng, John P. Lalor, and Hong Yu. A psychology-based unified dynamic framework for curriculum learning. *ArXiv*, abs/2408.05326, 2024.

Gemma Team Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, L. Sifre, Morgane Rivière, Mihir Kale, J Christopher Love, P. Tafti, L'eonard Hussenot, Aakanksha Chowdhery, Adam Roberts, Aditya Barua, Alex Botev, Alex Castro-Ros, Ambrose Slone, Am'elie H'eliou, Andrea Tacchetti, Anna Bulanova, Antonia Paterson, Beth Tsai, Bobak Shahriari, Charline Le Lan, Christopher A. Choquette-Choo, Clé ment Crepy, Daniel Cer, Daphne Ippolito, David Reid, Elena Buchatskaya, Eric Ni, Eric Noland, Geng Yan, George Tucker, George-Christian Muraru, Grig ory Rozhdestvenskiy, H. Michalewski, Ian Tenney, Ivan Grishchenko, Jacob Austin, James Keeling, Jane Labanowski, Jean-Baptiste Lespiau, J. Stanway, Jenny Brennan, Jeremy Chen, Johan Ferret, Justin Chiu, J. Mao-Jones, Kather ine Lee, Kathy Yu, Katie Millican, Lars Lowe Sjoesund, Lisa Lee, Lucas Dixon, Machel Reid, Maciej Mikuła, Mateo Wirth, Michael Sharman, Nikolai Chinaev, Nithum Thain, Olivier Bachem, Oscar Chang, O. Wahltinez, Paige Bailey, Paul Michel, Petko Yotov, Pier Giuseppe Sessa, Rahma Chaabouni, Ramona Comanescu, Reena Jana, Rohan Anil, Ross McIlroy, Ruibo Liu, Ryan Mullins, Samuel L Smith, Sebastian Borgeaud, Sertan Girgin, Sholto Douglas, Shree Pandya, Siamak Shakeri, Soham De, Ted Klimenko, Tom Hennigan, Vladimir Feinberg, Wojciech Stokowiec, Yu hui Chen, Zafarali Ahmed, Zhitao Gong, Tris Warkentin, Ludovic Peran, Minh Giang, Clément Farabet, O. Vinyals, Jeffrey Dean, K. Kavukcuoglu, D. Hassabis, Z. Ghahramani, Douglas Eck, Joelle Barral, Fernando Pereira, Eli Collins, Armand Joulin, Noah Fiedel, Evan Senter, Alek Andreev, and Kathleen Kenealy. Gemma: Open models based on gemini research and technology. *ArXiv*, abs/2403.08295, 2024.

B. Olshausen and D. Field. Emergence of simple-cell receptive field properties by learning a sparse code for natural images. *Nature*, 381:607–609, 1996.

OpenAI. Gpt-4 technical report, 2024. URL `https://arxiv.org/abs/2303.08774`.

Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32, 2019.

Leonardo Ranaldi, Giulia Pucci, and F. M. Zanzotto. Modeling easiness for training transformers with curriculum learning. pp. 937–948, 2023.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017.

D. Weinshall and Gad Cohen. Curriculum learning by transfer learning: Theory and experiments with deep networks. pp. 5235–5243, 2018.