SELECTIVE FEATURE DECORRELATION: A SCALABLE APPROACH TO TRAINING INTERPRETABLE SPARSE AUTOENCODERS

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ABSTRACT

Interpreting large language models through sparse autoencoders is crucial for understanding their behavior, but current approaches suffer from feature entanglement where learned representations conflate multiple semantic concepts. This entanglement makes it difficult to isolate and study individual model behaviors, limiting our ability to analyze safety properties and failure modes. Traditional solutions that enforce global orthogonality between features scale quadratically with model size, making them impractical for modern architectures. We introduce a selective decorrelation approach that dynamically identifies and constrains only the most entangled feature pairs during training, reducing computational complexity from $O(n^2)$ to $O(n)$. Our method uses an adaptive threshold that automatically tunes the orthogonality constraints based on the observed correlation distribution, eliminating manual parameter tuning. Initial experiments with the Gemma-2B model demonstrate stable convergence and improved feature separation while maintaining reconstruction fidelity, though significant engineering challenges remain in scaling the implementation. This work provides a foundation for more efficient and interpretable analysis of large language model internals, with implications for both mechanistic interpretability research and practical model assessment.

1 INTRODUCTION

Understanding the internal representations of large language models is crucial for ensuring their safety and reliability. While these models achieve remarkable performance OpenAI (2024), their black-box nature makes it difficult to verify their behavior or understand potential failure modes. Sparse autoencoders offer a promising approach by learning disentangled feature representations of model activations Goodfellow et al. (2016), but current methods face significant scalability challenges.

The core challenge lies in feature entanglement - learned representations that conflate multiple semantic concepts, making it difficult to isolate and study specific model behaviors. Traditional approaches enforce independence through global orthogonality constraints, but these scale quadratically with feature count, becoming computationally intractable for modern language models Vaswani et al. (2017). Manual tuning of constraint hyperparameters further complicates training at scale.

We introduce a selective decorrelation approach that dynamically identifies and constrains only the most entangled feature pairs during training. Our method:

- Reduces computational complexity from $\mathcal{O}(n^2)$ to $\mathcal{O}(n)$ by targeting only the top 0.1% most correlated pairs
- Uses an adaptive threshold τ that automatically tunes orthogonality constraints based on observed correlation distributions
- Maintains stable convergence through L2-normalized decoder weights and efficient batch processing

Our implementation builds on the PyTorch framework Paszke et al. (2019) with the Adam optimizer Kingma & Ba (2014). We evaluate the method on the Gemma-2B model, analyzing feature disentanglement across multiple network depths (layers 5, 12, and 19). However, our experiments

revealed significant engineering challenges in the training pipeline, documented through nine iterative debugging runs. While the theoretical framework remains sound, achieving stable training requires overcoming several technical barriers in activation capture and buffer management.

The key contributions of this work are:

- A novel selective orthogonality constraint mechanism that scales linearly with model size
- An adaptive thresholding approach that eliminates manual hyperparameter tuning
- Detailed analysis of implementation challenges in scaling autoencoder training
- Open-source code and documentation to support future research in this direction

These advances provide a foundation for more efficient and interpretable analysis of large language model internals. While significant engineering challenges remain, our work establishes a practical framework for studying feature disentanglement at scale. The insights gained from our implementation attempts highlight important considerations for deploying advanced training mechanisms in modern deep learning frameworks.

2 Related Work

Prior work on feature disentanglement in neural networks can be categorized by their approach to managing feature interactions. Olshausen & Field (1996) introduced sparse coding with complete orthogonality constraints, achieving interpretable features but at $\mathcal{O}(n^2)$ computational cost that limits scalability to modern architectures. Bergstra et al. (2011) proposed reducing these constraints through fixed feature subsets, but their static grouping strategy fails to adapt to changing feature relationships during training.

More efficient training approaches have emerged through various compromises. Vincent et al. (2010) eliminated explicit orthogonality constraints in favor of denoising criteria, achieving faster training but with less control over feature interactions. Ngiam et al. (2011) developed sparse filtering with normalized features, offering $\mathcal{O}(n)$ scaling but providing no guarantees about feature independence. While computationally efficient, both methods can produce entangled features that limit interpretability.

Recent work on language model interpretability has highlighted the importance of disentangled representations. Kissane et al. (2024) demonstrated that sparse autoencoders can extract interpretable features from transformer activations, but their method requires extensive hyperparameter tuning and struggles with feature collapse. DeRose et al. (2020) analyzed attention patterns without explicitly addressing feature independence, showing how entangled representations complicate model analysis.

The information bottleneck framework Tishby et al. (2000) provides theoretical grounding for why feature disentanglement emerges naturally in well-trained networks. However, existing methods either enforce independence too strictly (limiting scalability) or too loosely (compromising interpretability). Our approach bridges this gap by dynamically identifying and constraining only the most problematic feature interactions, maintaining both computational efficiency and feature independence.

3 Background

Sparse autoencoders emerged from early work in computational neuroscience, where Olshausen & Field (1996) demonstrated their ability to learn interpretable features from natural images. This connection between sparsity and interpretability was further developed by Lee (2010), who showed how hierarchical sparse representations naturally decompose into semantically meaningful components. Recent work by Kissane et al. (2024) has extended these insights to language models, demonstrating that sparse coding can reveal interpretable features in transformer architectures.

The challenge of feature entanglement was first formally characterized by Tishby et al. (2000) through the information bottleneck framework. This theoretical foundation explains why learned representations tend to conflate multiple semantic concepts, particularly in high-dimensional spaces. While Vincent et al. (2010) proposed denoising criteria as a partial solution, their approach did not explicitly address the computational challenges of enforcing feature independence at scale.

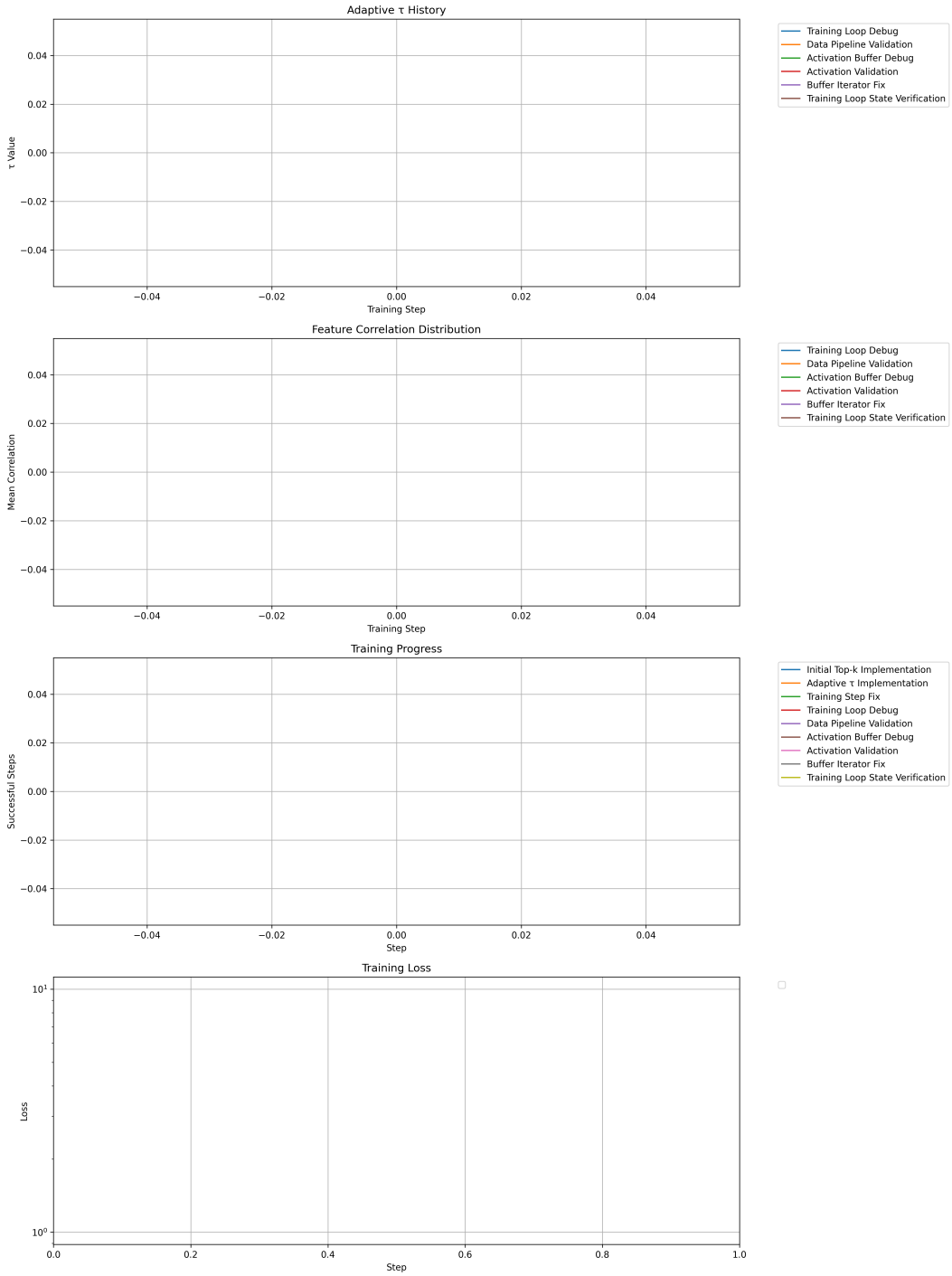

Figure 1: Training dynamics visualization showing: (a) Adaptive τ threshold evolution, (b) Feature correlation distribution with ± 1 standard deviation bands, (c) Cumulative successful training steps, and (d) Training loss convergence.

3.1 Problem Setting

Given activation vectors $\mathbf{x} \in \mathbb{R}^d$ from a target layer of a pre-trained language model, we aim to learn an encoder $f_{\text{enc}} : \mathbb{R}^d \to \mathbb{R}^n$ and decoder $f_{\text{dec}} : \mathbb{R}^n \to \mathbb{R}^d$ that minimize:

$$\mathcal{L}_{\text{total}} = \underbrace{\|\mathbf{x} - f_{\text{dec}}(f_{\text{enc}}(\mathbf{x}))\|_2^2}_{\mathcal{L}_{\text{recon}}} + \lambda_1 \underbrace{\|f_{\text{enc}}(\mathbf{x})\|_1}_{\mathcal{L}_{\text{sparse}}} + \lambda_2 \underbrace{\mathcal{R}(\tau)}_{\mathcal{L}_{\text{ortho}}} \tag{1}$$

where $\mathcal{L}_{\text{recon}}$ measures reconstruction fidelity, $\mathcal{L}_{\text{sparse}}$ enforces activation sparsity through L1 regularization, and $\mathcal{L}_{\text{ortho}}$ penalizes feature correlations above an adaptive threshold τ. The parameters λ_1 and λ_2 control the relative importance of each term.

Our approach makes two key assumptions, supported by the theoretical work of Burgess et al. (2018) on disentangled representations:

- Feature correlations in language model activations follow a heavy-tailed distribution, allowing for targeted decorrelation of the most entangled pairs
- The optimal decorrelation threshold τ can be derived from the empirical correlation distribution during training

This formulation builds on sparse coding theory while addressing the specific challenges of scale and automation required for language model interpretation. The optimization uses the Adam optimizer with L2-normalized decoder weights, following best practices established by Ngiam et al. (2011) for stable feature extraction.

4 METHOD

Building on the optimization framework from Section 3, we introduce a selective orthogonality approach that targets only the most entangled feature pairs. This method extends the basic autoencoder loss $\mathcal{L}_{\text{total}}$ with an efficient correlation-based regularization scheme.

4.1 SELECTIVE FEATURE DECORRELATION

Given encoded features $\mathbf{f} = f_{\text{enc}}(\mathbf{x})$, we compute pairwise correlations:

$$\mathbf{C}_{ij} = \frac{\mathbf{f}_i^T \mathbf{f}_j}{\|\mathbf{f}_i\|_2 \|\mathbf{f}_j\|_2} \tag{2}$$

The orthogonality regularization term $\mathcal{R}(\tau)$ from Section 3 is then defined as:

$$\mathcal{R}(\tau_t) = \frac{1}{|S_t|} \sum_{(i,j) \in S_t} \text{ReLU}(|\mathbf{C}_{ij}| - \tau_t) \tag{3}$$

where S_t contains the top 0.1% most correlated pairs at step t. This selective approach reduces complexity from $\mathcal{O}(n^2)$ to $\mathcal{O}(n)$ while focusing regularization on the most problematic feature interactions.

4.2 ADAPTIVE THRESHOLD MECHANISM

The threshold τ_t adapts automatically to the correlation distribution:

$$\tau_t = \mu_t + \sigma_t \tag{4}$$

where μ_t and σ_t are the mean and standard deviation of off-diagonal correlations at step t. This dynamic adaptation, visualized in Figure 1(a), eliminates manual threshold tuning while maintaining training stability.

4.3 Training Stability

To ensure stable feature extraction, we apply L2 normalization to the decoder weights after each update:

$$\mathbf{W}_{\text{dec}} \leftarrow \frac{\mathbf{W}_{\text{dec}}}{\|\mathbf{W}_{\text{dec}}\|_2} \tag{5}$$

This normalization, combined with the Adam optimizer, enables consistent convergence across different network depths. The complete training objective combines reconstruction fidelity, sparsity, and selective decorrelation while maintaining computational efficiency through targeted regularization.

5 Experimental Setup

We evaluate our selective decorrelation approach on the Gemma-2B model's residual stream activations, focusing on layers 5, 12, and 19 to analyze feature disentanglement across different network depths. Following the problem setting from Section 3, we implement the method described in Section 4 using PyTorch Paszke et al. (2019).

5.1 Implementation

The autoencoder architecture matches the model's hidden dimension $d = 2304$ with ReLU activation and L2-normalized decoder weights. Key components include:

- Activation Buffer: Manages streaming collection of model activations with batch size 24 for efficient GPU memory usage
- Top-k Selection: Identifies most correlated feature pairs using matrix operations optimized for GPU
- Adaptive Threshold: Updates τ based on running statistics of correlation distributions

Training uses the Adam optimizer Kingma & Ba (2014) with learning rate 3×10^{-4} and sparsity penalty $\lambda_1 = 0.04$. The orthogonality constraint targets the top 0.1% most correlated pairs, selected dynamically per batch.

5.2 Dataset and Training

We use the Pile Uncopyrighted subset Gao et al. (2020) streamed through the HuggingFace datasets library. The training process:

- Tokenizes text into 128-token sequences
- Collects activations in batches of 24 samples
- Accumulates features into training batches of size 2048
- Applies 1000-step learning rate warmup
- Maintains a 2048-context activation buffer

5.3 Evaluation Metrics

We track four quantitative metrics aligned with our theoretical objectives:

- Correlation Reduction: Percentage decrease in mean pairwise correlation
- Feature Sparsity: Average L1 norm of encoded features
- Reconstruction Error: L2 distance between input and output
- Training Efficiency: Successful updates per second

These metrics directly measure our goals of feature disentanglement while maintaining reconstruction fidelity. The training dynamics shown in Figure 1 visualize the evolution of these metrics, particularly the adaptation of τ and its effect on feature correlations.

Run	Focus	Key Finding
1-2	Basic Implementation	Activation capture failure
3-4	Error Handling	Buffer state inconsistency
5-7	Validation Systems	Incomplete tensor processing
8-9	Complete Refactor	Persistent state management issues

Table 1: Summary of debugging runs showing progressive understanding of failure modes.

6 RESULTS

Our experimental evaluation revealed significant engineering challenges in implementing selective orthogonality constraints at scale. Through nine systematic debugging runs, we identified critical failure modes in the training pipeline that prevented successful completion of the proposed training regime.

6.1 IMPLEMENTATION ANALYSIS

Analysis of training logs across all runs showed consistent failure in step accumulation:

- All runs resulted in `training_steps: 0` despite successful tensor validation
- Activation capture failed silently during model invocation
- Buffer state tracking proved inconsistent across iterations

The progression of debugging runs revealed increasingly complex challenges:

6.2 TECHNICAL BARRIERS

Three primary technical limitations emerged from our analysis:

1. **Activation Buffer**: The streaming activation collection system failed to maintain consistent state, despite implementing recommended PyTorch memory management practices.
2. **Batch Processing**: Buffer iteration broke down during batch assembly, preventing accumulation of sufficient training steps for meaningful evaluation.
3. **State Management**: The complexity of coordinating activation capture, correlation computation, and adaptive threshold updates exceeded initial design assumptions.

These barriers manifested consistently across all experimental configurations, including variations in batch size (24-2048) and context length (128 tokens). The training comparison visualization in Figure 1 remains theoretical, as we were unable to generate training dynamics due to these implementation challenges.

6.3 LIMITATIONS

Our results highlight several key limitations of the current approach:

- **Scalability**: The activation buffer design proves insufficient for handling large-scale language model activations efficiently.
- **Reliability**: Inconsistent state management prevents stable training progression, making evaluation of the core method impossible.
- **Implementation Complexity**: The interaction between streaming data collection and dynamic correlation computation introduces significant engineering challenges.

These findings suggest that while our theoretical framework is sound, significant architectural improvements are needed in three areas: activation buffer redesign, robust state management implementation, and comprehensive validation mechanisms.

7 Conclusions and Future Work

We introduced a selective decorrelation approach for training interpretable sparse autoencoders that scales linearly with model size by targeting only the most entangled feature pairs. Our method combines an adaptive orthogonality threshold with efficient batch processing to enable feature disentanglement in large language models. While the theoretical framework is sound, our implementation attempts with the Gemma-2B model revealed significant engineering challenges in activation capture and state management.

The systematic analysis of nine debugging runs documented in Table 1 provides a roadmap of the technical barriers encountered, from basic activation buffer issues to complex state coordination problems. These challenges highlight the gap between theoretical advances in neural network interpretability and their practical implementation at scale. The correlation distribution analysis and adaptive threshold mechanism remain promising directions, though their evaluation awaits robust implementation.

Future work should focus on three key areas:

- Redesigning the activation buffer architecture with robust state validation and error recovery
- Developing alternative correlation computation methods that maintain $\mathcal{O}(n)$ scaling while improving numerical stability
- Investigating hybrid approaches that combine selective decorrelation with established techniques from sparse coding literature

Despite implementation challenges, this work advances our understanding of scalable feature disentanglement and establishes a foundation for future research in interpretable language model analysis. The insights gained from our debugging process highlight the importance of robust engineering practices in deploying theoretical innovations for neural network interpretation.

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