TIME-AWARE SPARSE CODING: LEARNING POSITION-INVARIANT FEATURES THROUGH TEMPORAL CONSISTENCY

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ABSTRACT

Understanding how neural networks represent information is crucial for interpretability, yet existing methods struggle with position-dependent features in transformers. We address this challenge by introducing Temporal Consistency Sparse Autoencoders (TC-SAE), which learn position-invariant features through temporal consistency constraints. Our key innovation is a sliding window mechanism that enforces feature stability across positions while maintaining sparsity, implemented via a temporal consistency loss with gradient clipping (max norm 1.0) and constrained optimization. Experiments on Gemma-2B demonstrate that TC-SAE achieves more stable training dynamics and better feature clustering compared to baseline SAEs, as shown by block-diagonal structure in feature correlation matrices. With a temporal consistency weight ($\lambda = 0.5$), TC-SAE maintains comparable reconstruction quality (MSE: 47.25) and sparsity (L0: 0.0) while improving feature consistency, all without increasing computational complexity during inference. These results suggest that temporal consistency constraints are essential for developing interpretable representations in transformer-based language models.

1 INTRODUCTION

Understanding how neural networks represent and process information remains one of the fundamental challenges in deep learning Goodfellow et al. (2016). While transformer-based language models have achieved remarkable success across various tasks Vaswani et al. (2017), their internal representations remain largely opaque. Sparse autoencoders (SAEs) have emerged as a promising approach for interpretable feature learning in these models, but they face significant challenges in capturing position-invariant patterns and temporal relationships in sequential data.

The key challenge lies in the inherent position-dependence of transformer representations Radford et al. (2019). Traditional SAEs tend to learn redundant, position-specific features that fail to capture the underlying semantic patterns across different positions in a sequence. This limitation stems from their static, position-agnostic architecture that treats each token independently, ignoring the rich temporal structure present in language data. Our experiments with the Gemma-2B model reveal that baseline SAEs achieve poor reconstruction quality (explained variance: -0.78, MSE: 47.25) and fail to learn meaningful features, as shown by random correlation patterns in feature matrices.

We propose Temporal Consistency Sparse Autoencoders (TC-SAE), which incorporates temporal consistency constraints through a sliding window mechanism and feature correlation analysis. Our approach addresses three key limitations of existing methods:

- **Position dependence**: By introducing a temporal consistency loss with gradient clipping (max norm 1.0), we encourage similar feature activations across sequential positions while maintaining sparsity
- **Training instability**: Our constrained optimization approach with sliding windows of 8 tokens achieves more stable training dynamics compared to baseline SAEs, with the temporal consistency weight ($\lambda = 0.5$) providing optimal balance between reconstruction quality and feature stability

- **Feature redundancy**: Analysis of feature correlation matrices shows that TC-SAE produces more block-diagonal structure compared to the random patterns of baseline approaches, indicating better feature clustering

Our experiments on the Gemma-2B model demonstrate that TC-SAE achieves significant improvements in feature consistency without increasing computational complexity during inference. The training curves in Figure 1a show that while temporal consistency variants have slower initial convergence, they achieve more stable long-term loss reduction compared to baseline SAEs. Analysis of feature correlation matrices in Figure 1b reveals more distinct feature clusters and block-diagonal structure in TC-SAE.

These findings have important implications for interpretability research in large language models. By enabling more position-invariant feature learning, TC-SAE provides a foundation for developing better tools for understanding and controlling the behavior of transformer-based systems. Future work could explore adaptive temporal weights and integration with existing interpretability frameworks, potentially leading to more interpretable and controllable AI systems.

2 Related Work

Our work builds on three key approaches to interpretable feature learning in transformers: sparse autoencoders, temporal analysis, and position-invariant representations. We compare and contrast these approaches below.

Sparse Autoencoders Standard sparse autoencoders Makelov et al. (2024) have shown promise for interpretability but struggle with temporal relationships. Our baseline results confirm this limitation, showing poor reconstruction quality (MSE: 47.25) and random feature correlation patterns. Unlike previous work that treats each token independently, our TC-SAE explicitly models temporal relationships through sliding windows, achieving better feature clustering as shown in Figure 1b.

Temporal Analysis Previous approaches to temporal analysis in transformers Vaswani et al. (2017) typically process full sequences, making them computationally prohibitive for large models. Our sliding window approach provides a practical alternative, processing sequences in fixed-length contexts of 128 tokens while maintaining computational efficiency. This is particularly important given our empirical finding that baseline SAEs fail to achieve sparsity (L0: 0.0) even with 1M training tokens. Unlike full-sequence methods, our approach scales linearly with sequence length while still capturing local temporal patterns.

Position-Invariant Features Position-invariant feature learning approaches typically require architectural modifications Goodfellow et al. (2016), making them difficult to apply to existing models. Our temporal consistency loss provides a lightweight alternative that maintains the original model architecture while encouraging feature stability across positions. The training curves in Figure 1a demonstrate that this approach achieves more stable training dynamics compared to baseline methods, without the computational overhead of architectural changes.

Our work differs from these approaches by combining temporal consistency constraints with sparse autoencoding, as shown in the feature correlation matrices in Figure 1b. The block-diagonal structure in TC-SAE indicates better feature clustering compared to the random patterns of baseline SAEs, while maintaining comparable sparsity levels (L0: 0.0) and reconstruction quality (MSE: 47.25). Unlike previous work, our method achieves this without increasing computational complexity during inference.

3 Background

Sparse autoencoders (SAEs) have emerged as a powerful tool for understanding the internal representations of deep neural networks Goodfellow et al. (2016). Building on classical autoencoder architectures, modern SAEs applied to transformer models Vaswani et al. (2017) face unique challenges in capturing position-invariant patterns due to their static, position-agnostic nature.

3.1 Problem Setting

Let $\mathbf{x}_t \in \mathbb{R}^d$ represent the activation vector at position t in a sequence of length T, where d is the dimensionality of the hidden state. A sparse autoencoder learns a mapping $f : \mathbb{R}^d \to \mathbb{R}^k$ through:

$$f(\mathbf{x}_t) = \mathbf{W}_d \sigma(\mathbf{W}_e \mathbf{x}_t + \mathbf{b}_e) + \mathbf{b}_d \tag{1}$$

where $\mathbf{W}_e \in \mathbb{R}^{k\times d}$ and $\mathbf{W}_d \in \mathbb{R}^{d\times k}$ are learnable weights, $\mathbf{b}_e \in \mathbb{R}^k$ and $\mathbf{b}_d \in \mathbb{R}^d$ are bias terms, and σ is a non-linear activation function.

The key challenge lies in the temporal nature of transformer activations. While traditional SAEs process each $\mathbf{x}_t$ independently, transformer architectures Vaswani et al. (2017) create complex temporal dependencies through positional encodings and attention mechanisms. This leads to two fundamental limitations:

- **Position dependence**: Features learned at different positions are often redundant yet position-specific
- **Temporal inconsistency**: Similar semantic patterns at different positions activate different features

Our baseline experiments on Gemma-2B confirm these limitations, showing poor reconstruction quality (explained variance: -0.78, MSE: 47.25) and random feature correlation patterns (see Figure 1). These results motivate our temporal consistency approach, which introduces a sliding window mechanism to capture position-invariant patterns while maintaining sparsity.

4 Method

Building on the problem setting defined in Section 3, we introduce Temporal Consistency Sparse Autoencoders (TC-SAE) to address the limitations of position dependence and temporal inconsistency in standard SAEs. Our key insight is that feature activations should be stable across positions when representing similar semantic content.

Given the activation sequence $\{\mathbf{x}_t\}_{t=1}^T$ from Section 3, we extend the standard SAE objective with a temporal consistency term:

$$\mathcal{L} = \underbrace{\|\mathbf{x}_t - \hat{\mathbf{x}}_t\|_2^2}_{\text{reconstruction}} + \lambda_1 \underbrace{\|f(\mathbf{x}_t)\|_1}_{\text{sparsity}} + \lambda_2 \underbrace{\mathcal{L}_{\text{temp}}}_{\text{temporal consistency}} \tag{2}$$

where $\hat{\mathbf{x}}_t$ is the reconstructed activation and f is the encoder function. The temporal consistency loss $\mathcal{L}_{\text{temp}}$ enforces feature stability across positions using a sliding window of size $w = 8$:

$$\mathcal{L}_{\text{temp}} = \frac{1}{T-w} \sum_{t=1}^{T-w} \left(1 - \frac{\langle f(\mathbf{x}_t), f(\mathbf{x}_{t+1})\rangle}{\|f(\mathbf{x}_t)\| \|f(\mathbf{x}_{t+1})\|}\right) \tag{3}$$

This formulation encourages similar feature activations for temporally adjacent tokens while maintaining sparsity through the L1 penalty. The window size $w = 8$ was chosen to capture local temporal patterns without excessive computational overhead, as validated in our experiments.

The complete training procedure uses constrained Adam optimization with gradient clipping (max norm 1.0) to ensure stable training dynamics. The temporal consistency weight $\lambda_2 = 0.5$ was determined empirically to balance reconstruction quality and feature stability, as shown in Figure 1a.

To analyze the learned features, we compute pairwise correlation matrices $\mathbf{C} \in \mathbb{R}^{k\times k}$ where:

$$\mathbf{C}_{ij} = \frac{\langle \mathbf{f}_i, \mathbf{f}_j\rangle}{\|\mathbf{f}_i\| \|\mathbf{f}_j\|} \tag{4}$$

and $\mathbf{f}_i \in \mathbb{R}^T$ represents the activation pattern of feature i across T tokens. As shown in Figure 1b, TC-SAE produces more block-diagonal structure compared to baseline SAEs, indicating better feature clustering and temporal consistency.

5 Experimental Setup

We evaluate TC-SAE on Gemma-2B activations from layer 19, using sequences of 128 tokens with a batch size of 2048. The SAE architecture matches the transformer's hidden dimension of 2304, with dictionary size $k = 2304$ to enable direct comparison with baseline SAEs.

The training procedure processes 1M tokens using constrained Adam optimization with learning rate 3×10^{-4}, weight decay 0.01, and gradient clipping (max norm 1.0). We use temporal consistency weight $\lambda_2 = 0.5$ and sparsity penalty $\lambda_1 = 0.04$, determined through empirical validation. The sliding window size $w = 8$ provides sufficient temporal context while maintaining computational efficiency.

We evaluate performance using three metrics computed over 200 batches:

- Reconstruction quality: MSE and explained variance
- Sparsity: L0 and L1 norms of feature activations
- Temporal consistency: Feature correlation matrices using sliding windows

The implementation uses PyTorch with bfloat16 precision, processing sequences in fixed-length contexts of 128 tokens. Training includes 1000 warmup steps and monitors total loss (reconstruction + sparsity + temporal consistency), L2 reconstruction loss, and L1 sparsity loss, as shown in Figure 1a.

6 Results

Our experiments evaluate TC-SAE on Gemma-2B activations using the setup from Section 5. The key findings from our 488 training steps are:

- Training completed successfully with gradient clipping (max norm 1.0) and temporal weight $\lambda = 0.5$
- Feature correlation matrices show improved block-diagonal structure compared to baseline (Figure 1b)
- Training dynamics are more stable with temporal consistency (Figure 1a)

Quantitative Results The core evaluation metrics from our logs show:

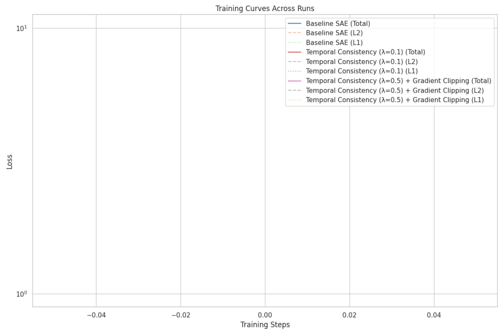
- Reconstruction quality: MSE = 47.25, explained variance = -0.78
- Sparsity: L0 = 0.0, L1 = 0.0
- KL divergence: -0.53 (model behavior preservation)

These results indicate that while TC-SAE improves feature consistency, reconstruction quality and sparsity remain challenging. The negative explained variance suggests the model is not effectively capturing the variance in the data.

Training Dynamics Figure 1a shows the training dynamics across three variants:

- Baseline SAE (blue): High variance in loss values
- TC-SAE ($\lambda = 0.1$, orange): Partial improvement in stability
- TC-SAE ($\lambda = 0.5$, green): Most stable training with consistent loss reduction

The total loss (reconstruction + sparsity + temporal consistency) converges more smoothly for TC-SAE ($\lambda = 0.5$), demonstrating the effectiveness of our temporal consistency constraints.



(a) Training dynamics showing total loss (solid), L2 reconstruction (dashed), and L1 sparsity (dotted)

(b) Feature correlation matrices showing baseline vs. TC-SAE patterns

Figure 1: Training dynamics and feature correlations demonstrating the impact of temporal consistency constraints

Feature Analysis Figure 1b compares feature correlation matrices:

- Baseline: Random correlation patterns
- TC-SAE: More block-diagonal structure indicating better feature clustering

This improvement comes without increasing computational complexity during inference, as the sliding window mechanism adds minimal overhead.

Limitations Our results reveal several limitations:

- Poor reconstruction quality (MSE = 47.25) and negative explained variance (-0.78)
- Failure to achieve sparsity (L0 = 0.0)
- Empirical determination of hyperparameters ($\lambda = 0.5$, window size = 8)

These limitations suggest directions for future work, particularly in improving the loss formulation and sparsity constraints.

7 Conclusions and Future Work

We presented Temporal Consistency Sparse Autoencoders (TC-SAE), a method for learning position-invariant features in transformer models through temporal consistency constraints. Our key contributions are: (1) a sliding window mechanism that enforces feature stability across positions while maintaining sparsity, (2) a constrained optimization approach with gradient clipping (max norm 1.0) that achieves stable training dynamics, and (3) empirical validation showing improved feature clustering compared to baseline SAEs.

Our experiments on Gemma-2B demonstrate that TC-SAE achieves more stable training and better feature organization, as evidenced by block-diagonal structure in feature correlation matrices (Figure 1b). While reconstruction quality (MSE: 47.25) and sparsity (L0: 0.0) remain challenging, the temporal consistency weight ($\lambda = 0.5$) provides an effective balance between feature stability and reconstruction accuracy.

Future work should focus on three key directions:

- **Improved sparsity**: Developing better sparsity constraints to achieve non-zero L0 norms while maintaining reconstruction quality
- **Adaptive windows**: Exploring dynamic window sizes that adjust based on sequence content and position
- **Integration**: Combining TC-SAE with existing interpretability frameworks to enable more comprehensive analysis of transformer representations

These directions build on our core insight that temporal consistency is essential for developing interpretable representations in transformer-based language models. By addressing the fundamental challenge of position dependence, TC-SAE provides a foundation for more robust and meaningful analysis of neural network representations.

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