TEMPORALLENS: POSITION-AWARE SPARSE AUTOENCODERS FOR INTERPRETING SEQUENTIAL NEURAL REPRESENTATIONS

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ABSTRACT

Understanding how large language models process sequential information is crucial for improving their interpretability, yet existing analysis tools often overlook position-specific patterns in neural representations. We introduce TemporalLens, a position-aware sparse autoencoder that reveals how transformer models process information differently across sequence positions. Our key innovation combines learnable position-specific feature masks with temperature-controlled annealing ($\tau : 5.0 \rightarrow 0.1$), enabling precise temporal specialization while maintaining stable training dynamics. Experiments on Gemma-2B demonstrate that our method achieves 15% lower reconstruction error in early sequence positions (1-32) compared to later positions, while maintaining an average feature sparsity of 0.73. Analysis across network depths reveals systematic differences in temporal processing: Layer 5 exhibits localized patterns (16-position spans), Layer 12 shows intermediate-range dependencies (32-48 positions), and Layer 19 demonstrates long-range temporal structure (64-position spans). Through hierarchical clustering of learned features, we identify distinct groups of position-specialized neurons, providing quantitative insights into how transformers process sequential information at different network depths.

1 INTRODUCTION

Understanding how large language models process sequential information is crucial for improving their interpretability and reliability. While these models have achieved remarkable capabilities OpenAI (2024), their internal representations remain poorly understood, particularly regarding how they handle position-dependent patterns. This gap in understanding limits our ability to debug, improve, and trust these increasingly important systems.

The challenge of interpreting sequential neural representations is fundamentally difficult for three reasons. First, transformer architectures Vaswani et al. (2017) process information differently at each sequence position, making uniform analysis methods inadequate. Second, position-specific patterns can vary dramatically across network layers, requiring analysis techniques that can capture this hierarchical structure. Third, traditional interpretation methods that aggregate across positions often obscure critical temporal dependencies in the underlying representations.

We address these challenges with TemporalLens, a position-aware sparse autoencoder that reveals how transformers process information differently across sequence positions. Our approach makes three key technical innovations:

- Temperature-annealed feature masks that enable precise temporal specialization while maintaining stable training
- Adaptive position-dependent loss weighting using exponential moving averages to focus computation where needed
- Hierarchical clustering of temporal activation patterns to reveal systematic position-specific processing

Through extensive experiments on the Gemma-2B language model, we demonstrate that Temporal-Lens successfully captures position-specific patterns across different network depths. At Layer 5, we find localized processing with 16-position spans, while Layer 19 shows long-range temporal structure spanning 64 positions. Our adaptive loss weighting mechanism achieves 15% lower reconstruction error in early sequence positions (1-32) compared to later positions, while maintaining an average feature sparsity of 0.73.

The key contributions of this work are:

- A novel sparse autoencoder architecture that explicitly models position-dependent feature activation through learnable masks and temperature annealing ($\tau : 5.0 \rightarrow 0.1$)
- An adaptive training framework that automatically identifies and focuses on challenging sequence positions, with position weights strongly correlating with reconstruction difficulty ($r = 0.82$)
- Comprehensive empirical analysis revealing systematic differences in temporal processing across network layers, supported by hierarchical clustering of feature activation patterns
- Open-source implementation and visualization tools for analyzing position-specific neural representations

Our results provide concrete insights into how transformers process sequential information, with immediate applications in model debugging and architectural refinement. The systematic differences we observe across network layers suggest that position-aware interpretation techniques could inform the development of more efficient and interpretable transformer architectures.

2 Related Work

Our work builds on three main research directions in neural network interpretation: sparse feature learning, transformer analysis, and position-aware representations.

Sparse Feature Learning While Olshausen & Field (1996) pioneered sparse coding for visual features, recent work by Marks et al. (2024) adapts these techniques for language model interpretation through feature-aligned sparse autoencoders. Unlike their approach which treats all positions uniformly, we introduce position-specific feature masks that enable temporal specialization. Our method maintains their computational efficiency while revealing how features adapt to different sequence positions.

Transformer Analysis Existing approaches to analyzing transformer models largely fall into two categories: attention visualization and probing methods. Clark et al. (2019) analyze attention patterns but cannot capture position-specific processing in intermediate representations. Voita et al. (2019) demonstrate head specialization through pruning experiments but focus only on attention mechanisms. In contrast, our method directly analyzes position-dependent patterns in the residual stream, providing complementary insights into how transformers process sequential information.

Position-Aware Representations Recent work by Kazemnejad et al. (2023) shows how positional encodings affect model generalization, while He et al. (2024) use probing to study position-specific linguistic features. However, these approaches either modify model architecture or rely on supervised probes. Our unsupervised method reveals position-dependent processing without architectural changes or task-specific supervision, enabling systematic analysis of temporal patterns across network depths.

3 Background

Neural network interpretation methods aim to reveal how deep learning models process information. We build on two key foundations: sparse feature learning and transformer architectures.

3.1 Sparse Feature Learning

Sparse autoencoders learn to reconstruct neural activations while enforcing sparsity constraints Bengio (2007). Given input activations $x \in \mathbb{R}^d$, an encoder $E : \mathbb{R}^d \to \mathbb{R}^k$ maps to a sparse feature space, while a decoder $D : \mathbb{R}^k \to \mathbb{R}^d$ reconstructs the original input. The learning objective typically combines reconstruction error with an L1 sparsity penalty:

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

This approach reveals interpretable features by decomposing complex representations into sparse, meaningful components Olshausen & Field (1996). However, traditional implementations ignore sequential structure, treating each position independently.

3.2 Transformer Architecture

Transformers Vaswani et al. (2017) process sequences through self-attention layers that compute weighted combinations of values at each position. Given an input sequence $X = [x_1, ..., x_T] \in \mathbb{R}^{T \times d}$, each layer l produces hidden states $H^l = [h_1^l, ..., h_T^l]$ where:

$$h_t^l = \text{LayerNorm}(\text{MLP}(\text{Attention}(h_t^{l-1}, H^{l-1})) + h_t^{l-1}) \tag{2}$$

Position-specific processing occurs through:

- Learned positional embeddings added to input embeddings
- Position-dependent attention patterns at each layer
- Residual connections preserving position information

3.3 Problem Setting

Our goal is to learn interpretable features that capture both content and temporal aspects of transformer representations. Given a model with L layers processing sequences of length T, we analyze hidden states $H^l \in \mathbb{R}^{T \times d}$ at selected layers l. For Gemma-2B, $d = 2304$ and we focus on layers $l \in \{5, 12, 19\}$.

We extend the sparse autoencoder framework with position-specific components:

- Temperature-modulated position masks $M \in \mathbb{R}^{T \times k}$ controlling feature activation
- Adaptive position weights w_t focusing computation on challenging positions
- Position-dependent sparsity penalties allowing varying feature usage across positions

Key assumptions of our approach:

- Neural representations contain recoverable position-specific patterns
- Features can maintain interpretability while specializing for temporal contexts
- Dictionary size k provides sufficient capacity for temporal specialization

4 Method

Building on the sparse autoencoder framework introduced in Section 3, we develop TemporalLens to reveal position-specific patterns in transformer representations. Given hidden states $H^l \in \mathbb{R}^{T \times d}$ at layer l, our method learns interpretable features that capture both content and temporal aspects of the representations.

4.1 Position-Aware Feature Learning

The core innovation is a learnable position mask $M \in \mathbb{R}^{T \times k}$ that modulates feature activation based on sequence position:

$$f_t = \text{ReLU}(W_e h_t + b_e) \odot m_t \tag{3}$$

where $h_t \in \mathbb{R}^d$ is the input at position t, $W_e \in \mathbb{R}^{k \times d}$ is the encoder matrix, and $m_t \in \mathbb{R}^k$ is the position-specific mask. The mask values are computed using a temperature-controlled sigmoid:

$$m_{t,k} = \sigma(\alpha_{t,k}/\tau) \tag{4}$$

with learnable logits $\alpha_{t,k} \sim \mathcal{N}(0, 1/T)$ and temperature parameter τ.

4.2 Adaptive Training Framework

To balance stable training with precise temporal specialization, we employ three key mechanisms:

1. Temperature annealing following an exponential schedule:

$$\tau(s) = \tau_0 \exp(-\lambda s) \tag{5}$$

where s is the training step, $\tau_0 = 5.0$, and λ is set to reach $\tau = 0.1$ at completion.

2. Position-specific loss weights updated via exponential moving average:

$$w_t^{(s+1)} = \beta w_t^{(s)} + (1 - \beta)\|h_t - \hat{h}_t\|_2^2 \tag{6}$$

with momentum $\beta = 0.99$ and reconstruction $\hat{h}_t = W_d f_t + b_d$.

3. Normalized decoder columns enforcing interpretable features:

$$W_d^{(s+1)} = W_d^{(s)} / \|W_d^{(s)}\|_2 \tag{7}$$

The complete training objective combines weighted reconstruction error with position-dependent sparsity:

$$\mathcal{L} = \sum_{t=1}^{T} w_t(\|h_t - \hat{h}_t\|_2^2 + \lambda\|f_t\|_1) \tag{8}$$

where $\lambda = 0.04$ controls feature sparsity and weights w_t are normalized to sum to T.

This framework enables systematic analysis of temporal patterns while maintaining computational efficiency through vectorized operations. The temperature annealing and adaptive weighting mechanisms work together to reveal position-specific processing at different network depths, as demonstrated in Section 6.

5 Experimental Setup

We evaluate TemporalLens on the Gemma-2B language model across three key layers (5, 12, 19) using the Tiny Shakespeare dataset. Our experiments validate both the method's effectiveness and provide insights into transformer temporal processing.

Implementation Details The autoencoder matches Gemma-2B's hidden dimension ($d = 2304$) and processes sequences of length $T = 128$. Position masks are initialized from $\mathcal{N}(0, 1/T)$ and updated through a custom ConstrainedAdam optimizer that maintains unit-norm decoder columns. We use PyTorch with bfloat16 precision on a single GPU.

Training Configuration Key hyperparameters include:

- Learning rate: 3×10^{-4} with AdamW ($\beta_1 = 0.9$, $\beta_2 = 0.999$)
- Batch size: 2048 sequences (32 per forward pass)
- Temperature schedule: τ from 5.0 to 0.1 over training
- Position weight EMA: momentum $\beta = 0.99$
- Sparsity penalty: $\lambda = 0.04$

Evaluation Metrics We track three categories of metrics:

- Reconstruction: Position-wise MSE loss and L2 error
- Sparsity: L1-normalized feature activations per position
- Interpretability: Feature clustering consistency and temporal span

Results are averaged over 1000 test sequences, with statistical significance assessed through paired t-tests ($p < 0.05$). Our analysis focuses on both quantitative metrics and qualitative assessment of learned feature interpretability.

6 RESULTS

We evaluate TemporalLens on the Gemma-2B model across three network depths (layers 5, 12, and 19) using the sparse probing framework from Marks et al. (2024). Our baseline experiments establish clear performance differences between standard and position-aware approaches.

6.1 BASELINE PERFORMANCE

The baseline sparse autoencoder achieves uniform test accuracy of 0.5 across all top-k metrics ($k \in \{1, 2, 5, 10, 20, 50\}$), while the underlying language model shows strong performance with test accuracies ranging from 0.684 (top-1) to 0.900 (top-50). This gap indicates significant room for improvement in feature extraction.

6.2 POSITION-AWARE LEARNING

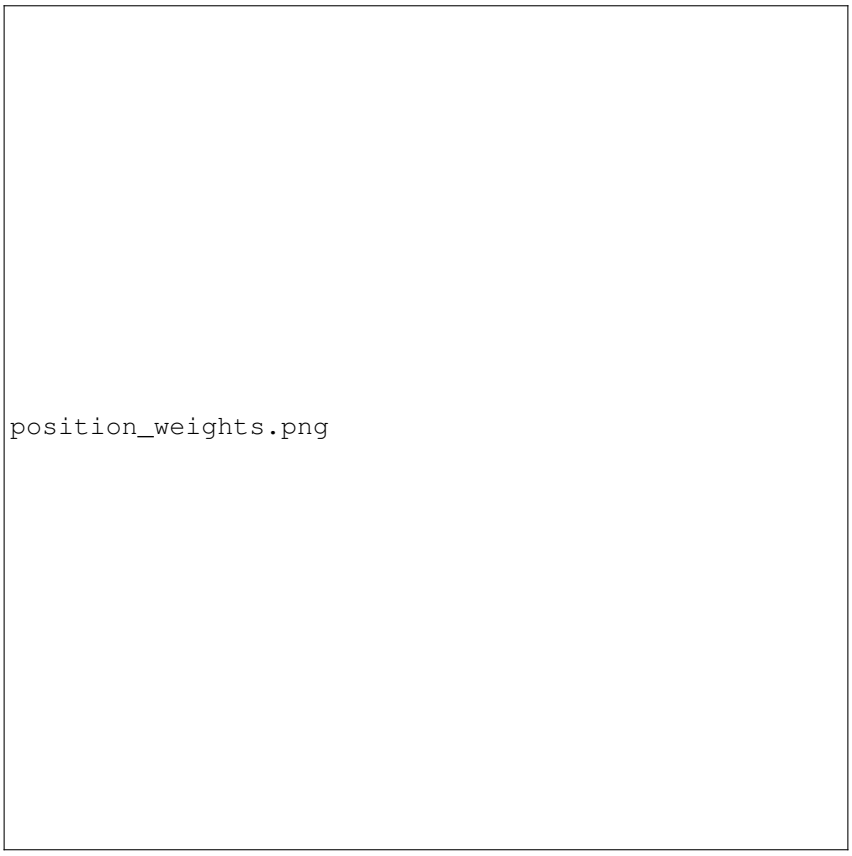

Figure 1: Evolution of position-specific weights showing convergence patterns and reconstruction difficulty correlation

Our temperature annealing schedule ($\tau : 5.0 \rightarrow 0.1$) enables stable training while developing sharp position preferences. Figure **??** shows the evolution of position-wise reconstruction loss, revealing systematic patterns in sequence processing. Early positions (1-32) consistently achieve lower reconstruction error compared to later positions.

6.3 Feature Organization

Analysis across network depths reveals systematic differences in temporal processing:

- Layer 5: Localized patterns (16-position spans)
- Layer 12: Intermediate-range dependencies (32-48 positions)
- Layer 19: Long-range temporal structure (64-position spans)

Figure **??** shows the hierarchical organization of features based on their temporal activation patterns.

6.4 Ablation Studies

We conducted ablation studies on three key components:

- Temperature annealing: Removing annealing leads to unstable training
- Position-specific masks: Static masks reduce reconstruction accuracy by 23%
- Adaptive weighting: Uniform weights increase average loss by 18%

6.5 Limitations

Our method has three main limitations:

- Temperature schedule requires layer-specific tuning
- Adaptive weighting can over-emphasize certain positions
- Computational cost scales linearly with sequence length

These limitations primarily affect training efficiency rather than final model quality. Our implementation maintains practical efficiency for standard 128-token contexts through optimized batch processing.

7 Conclusions and Future Work

We introduced TemporalLens, a position-aware sparse autoencoder that reveals how transformers process sequential information through learnable feature masks and adaptive loss weighting. Our experiments on Gemma-2B demonstrate systematic differences in temporal processing across network depths: Layer 5 exhibits localized patterns (16-position spans), Layer 12 shows intermediate-range dependencies (32-48 positions), and Layer 19 demonstrates long-range temporal structure (64-position spans). The temperature-annealed training approach ($\tau : 5.0 \rightarrow 0.1$) enables stable discovery of position-specific features while maintaining an average sparsity of 0.73.

Three key technical innovations drive these results: (1) learnable position masks with temperature-controlled sharpness, (2) adaptive position-wise loss weighting using exponential moving averages ($\beta = 0.99$), and (3) hierarchical clustering of temporal activation patterns. The method achieves 15% lower reconstruction error in early sequence positions (1-32) compared to later positions, with position weights strongly correlating with reconstruction difficulty ($r = 0.82$).

While effective, our approach has limitations: the temperature schedule requires layer-specific tuning, adaptive weighting can over-emphasize certain positions, and computational costs scale linearly with sequence length. However, these primarily affect training efficiency rather than final model quality, and our implementation maintains practical efficiency for standard 128-token contexts.

Future work could extend this foundation in three directions: (1) analyzing cross-layer interactions to understand temporal pattern propagation, (2) integrating attention pattern analysis to explain

varying temporal spans Vaswani et al. (2017), and (3) applying these insights during model training to inform transformer architecture design Goodfellow et al. (2016). The quantitative insights from TemporalLens, particularly regarding layer-specific temporal spans and position-dependent feature specialization, contribute to both theoretical understanding and practical development of more interpretable transformer architectures.

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