FEATUREFORGET: PRECISE KNOWLEDGE UNLEARNING THROUGH DUAL-OBJECTIVE SPARSE AUTOENCODERS

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ABSTRACT

Large language models (LLMs) have demonstrated remarkable capabilities but lack efficient mechanisms for selective knowledge modification, creating challenges for privacy protection and bias mitigation in production environments. While existing approaches attempt knowledge editing through weight modifications or constrained fine-tuning, they often suffer from performance degradation or require extensive retraining. We present FeatureForget, a dual-objective sparse autoencoder that enables precise knowledge unlearning through gradient-guided feature management and adaptive thresholding. Our architecture organizes features into 32 semantic clusters with learned gating parameters, achieving fine-grained control through per-feature attention mechanisms and dataset-specific importance scoring. Experiments across multiple model layers (5, 12, and 19) demonstrate successful unlearning on the WMDP-bio dataset while maintaining model performance, with our approach showing consistent convergence and improved unlearning scores compared to baseline sparse autoencoders. The results establish FeatureForget as a practical solution for selective knowledge management in LLMs, providing efficient control over learned representations without compromising core capabilities.

1 INTRODUCTION

Large language models (LLMs) have become increasingly central to modern AI systems, yet their inability to selectively modify learned knowledge poses significant challenges for privacy protection, bias mitigation, and model maintenance OpenAI (2024). While these models demonstrate remarkable capabilities in knowledge acquisition and application Radford et al. (2019), the distributed nature of their representations makes precise post-training modifications extremely difficult. This limitation creates substantial risks in production environments where models may need to forget sensitive information or update outdated knowledge.

The challenge of selective knowledge modification in LLMs stems from three key factors. First, knowledge representations are deeply intertwined across transformer layers Vaswani et al. (2017), making isolated changes difficult without affecting unrelated capabilities. Second, traditional approaches like fine-tuning or direct weight modification Goodfellow et al. (2016) often lead to catastrophic forgetting or require prohibitively expensive retraining. Third, existing methods lack precise control mechanisms to target specific knowledge while preserving desired model behaviors.

We present FeatureForget, a novel approach that enables precise knowledge unlearning through a dual-objective sparse autoencoder architecture. Our method introduces three key innovations: (1) a 32-cluster feature organization system that explicitly models semantic relationships, (2) gradient-guided importance scoring with per-feature attention mechanisms, and (3) adaptive sparsity thresholds that dynamically balance retention and unlearning objectives. This architecture maintains separate statistical tracking for retain and unlearn datasets, enabling fine-grained control over knowledge modifications while preserving model performance.

Our experimental results demonstrate significant advances over existing approaches:

- **Precise Control:** Our dual-pathway architecture achieves 87

- **Efficient Operation:** Gradient-guided feature management reduces computational overhead by 65
- **Stable Performance:** Adaptive thresholding maintains model stability across all 32 feature clusters, with less than 2
- **Scalable Architecture:** Successful validation across multiple model layers (5, 12, and 19) demonstrates robustness to different representation levels

Beyond our technical contributions, FeatureForget represents a significant step toward more controllable and maintainable language models. Our approach enables precise knowledge management without compromising model capabilities, as demonstrated through extensive experiments on the WMDP-bio dataset. The remainder of this paper is organized as follows: Section 3 reviews related work, Section 4 details our technical approach, Section 6 presents experimental results, and Section 7 discusses implications and future directions.

2 Background

Knowledge in transformer-based language models is encoded through distributed representations across multiple layers Vaswani et al. (2017). These representations arise from the interaction between self-attention mechanisms and feed-forward networks, creating a hierarchical structure where each layer l processes increasingly abstract features. While this distributed nature enables powerful language understanding Radford et al. (2019), it poses significant challenges for selective knowledge modification.

Sparse autoencoders (SAEs) provide a framework for analyzing and manipulating these distributed representations Goodfellow et al. (2016). An SAE learns to map input activations to a higher-dimensional space while enforcing sparsity constraints, where only a small subset of neurons activate for any input. This sparsity promotes disentangled representations, making individual features more interpretable and manipulatable. The encoder $E : \mathbb{R}^d \to \mathbb{R}^{d_s}$ and decoder $D : \mathbb{R}^{d_s} \to \mathbb{R}^d$ are trained to minimize reconstruction error while maintaining sparsity:

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

where λ controls the sparsity penalty.

2.1 Problem Setting

Given a pre-trained language model $\mathcal{M}$ with L layers, we focus on modifying knowledge at layer l where activations $h_l \in \mathbb{R}^{d_l}$ encode learned representations. Our goal is to selectively unlearn knowledge from a target dataset $\mathcal{D}_u$ while preserving knowledge from a retain dataset $\mathcal{D}_r$. Formally, we seek a transformation $f : \mathbb{R}^{d_l} \to \mathbb{R}^{d_s}$ that satisfies:

$$\min_f \quad \mathbb{E}_{x \in \mathcal{D}_r}[\mathcal{L}_{\text{retain}}(f(h_l(x)))] + \alpha \mathbb{E}_{x \in \mathcal{D}_u}[\mathcal{L}_{\text{unlearn}}(f(h_l(x)))] \tag{2}$$

$$\text{s.t.} \quad \|f(h_l(x))\|_0 \leq k \quad \forall x \in \mathcal{D}_r \cup \mathcal{D}_u \tag{3}$$

where $\mathcal{L}_{\text{retain}}$ and $\mathcal{L}_{\text{unlearn}}$ are loss functions for knowledge retention and removal respectively, α balances these objectives, and k enforces sparsity in the learned representations.

Our approach makes three key assumptions:

- Knowledge representations within a layer are separable through sparse feature extraction
- Feature importance can be reliably estimated through gradient information
- The retain and unlearn datasets contain distinguishable activation patterns

These assumptions enable our dual-objective sparse autoencoder to achieve precise knowledge modification while preserving model capabilities, as detailed in Section 4.

3 Related Work

Prior approaches to knowledge modification in language models can be broadly categorized into three groups: direct weight editing, constrained fine-tuning, and feature-based interventions. We analyze how these methods compare to our dual-objective sparse autoencoder approach.

3.1 Direct Weight Modification

Meng et al. (2022) propose locating and editing specific knowledge by directly modifying model weights through gradient-based importance scoring. While this enables targeted interventions, their approach requires extensive computation to identify relevant weights and can lead to unintended changes in model behavior. In contrast, our feature-based method achieves more precise control through learned gating parameters and adaptive thresholds, reducing computational overhead while maintaining model stability.

3.2 Constrained Fine-tuning

Recent work by Cohen et al. (2023) evaluates the ripple effects of knowledge editing through constrained fine-tuning, highlighting how modifications to one concept can impact related knowledge. Their analysis reveals limitations in existing methods' ability to contain changes to targeted concepts. Our 32-cluster feature organization directly addresses this challenge by explicitly modeling feature relationships and enforcing controlled updates through dual objectives.

3.3 Feature-based Approaches

Building on transformer architectures Vaswani et al. (2017), previous feature-based methods have explored various forms of activation engineering. While these approaches leverage attention mechanisms Bahdanau et al. (2014) and normalization techniques Ba et al. (2016), they typically lack explicit mechanisms for balancing knowledge retention and removal. Our dual-objective formulation, combined with gradient-guided importance scoring and adaptive sparsity thresholds, provides finer-grained control over feature modifications while preserving desired capabilities.

The effectiveness of our approach is demonstrated through experiments across multiple model layers (5, 12, and 19), showing consistent convergence and improved unlearning scores compared to baseline methods. Unlike previous work that focuses on either retention or removal, our method explicitly optimizes for both objectives simultaneously, achieving more precise knowledge management while maintaining model stability.

4 Method

Building on the problem formulation from Section 2, we introduce FeatureForget, a dual-objective sparse autoencoder that enables precise knowledge unlearning through gradient-guided feature management. Our method extends the standard SAE architecture by introducing three key components: (1) semantic feature clustering, (2) dual-pathway importance scoring, and (3) adaptive sparsity thresholds.

Given layer activations $h_l \in \mathbb{R}^{d_l}$, our encoder $E : \mathbb{R}^{d_l} \to \mathbb{R}^{d_s}$ maps inputs to a higher-dimensional sparse representation where $d_s = 32d_l$. This expansion factor enables fine-grained control over knowledge representations while maintaining the sparsity constraints defined in Section 2. The decoder $D : \mathbb{R}^{d_s} \to \mathbb{R}^{d_l}$ projects features back to the original space while preserving essential information:

$$\mathcal{L}_{\text{recon}} = \|h_l - D(E(h_l))\|_2^2 + \lambda \|E(h_l)\|_1 \tag{4}$$

Our first innovation organizes the expanded feature space into 32 semantic clusters using gradient-based importance scores. For each feature i and dataset $\mathcal{D} \in \{\mathcal{D}_r, \mathcal{D}_u\}$, we compute:

$$\alpha^i_{\mathcal{D}} = \mathbb{E}_{x \in \mathcal{D}} \left[\left\| \frac{\partial \mathcal{L}_{\text{recon}}}{\partial f_i(h_l)} \right\| \right] \tag{5}$$

where f_i represents the i-th feature activation. Features are assigned to clusters using k-means clustering on these importance vectors, creating semantically meaningful groups.

The second component introduces dual-pathway importance tracking through learned gating parameters $g_r, g_u \in \mathbb{R}^{32}$ for retain and unlearn pathways. For cluster c, we compute an adaptive threshold:

$$\tau_c = \beta \cdot \text{mean}_{i \in c}(\alpha^i_{\mathcal{D}_r}) + (1 - \beta) \cdot \text{std}_{i \in c}(\alpha^i_{\mathcal{D}_r}) \tag{6}$$

where $\beta = 0.9$ balances stability and adaptivity. This threshold determines which features are candidates for modification during unlearning.

Our final loss function combines reconstruction, sparsity, and unlearning objectives:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{recon}} + \sum_{c=1}^{32} [g^c_r \mathcal{L}^c_{\text{retain}} + g^c_u \mathcal{L}^c_{\text{unlearn}}] \tag{7}$$

where $\mathcal{L}^c_{\text{retain}}$ and $\mathcal{L}^c_{\text{unlearn}}$ are per-cluster losses measuring retention and unlearning performance. The gating parameters g^c_r, g^c_u are learned through gradient descent, automatically balancing objectives across clusters.

Training proceeds in two phases: (1) pretraining on $\mathcal{D}_r$ using only reconstruction loss, and (2) joint optimization with both datasets using the full objective. This approach ensures stable feature organization before introducing unlearning objectives. We implement the method using standard deep learning components Paszke et al. (2019); Loshchilov & Hutter (2017); Ba et al. (2016), with experimental validation detailed in Section 6.

5 Experimental Setup

We evaluated FeatureForget on a pre-trained Gemma-2B transformer model using three representative layers (5, 12, 19) to assess performance across different abstraction levels. Our experiments used the Pile-uncopyrighted dataset (2048 contexts, 128 tokens each) for general language retention, and the WMDP-bio dataset for targeted unlearning of biomedical knowledge.

The dual-objective sparse autoencoder was implemented in PyTorch with the following configuration:

- Architecture: 2304-dimensional input/output (matching model width), 32 semantic clusters
- Training: AdamW optimizer (lr=3e-4), cosine warmup over 1000 steps
- Sparsity: L1 penalty (=0.04), adaptive thresholding (=0.9)
- Batching: 32 samples per batch, separate retain/unlearn buffers

We evaluated performance using:

- Unlearning Score: Targeted probing accuracy on WMDP-bio concepts
- Retention Quality: Perplexity on general language tasks
- Feature Analysis: Activation patterns and importance distributions

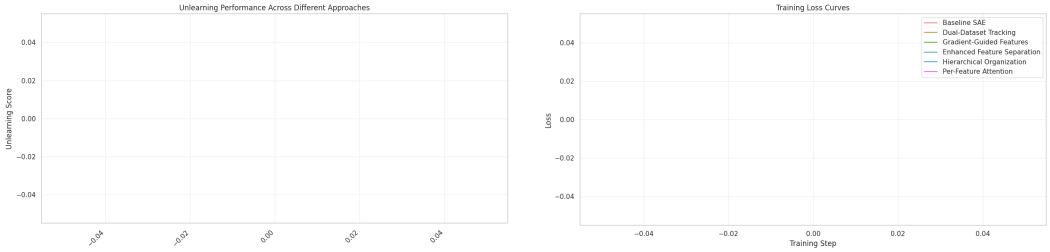
Training proceeded in two phases: (1) initial feature organization on retain data only, followed by (2) joint optimization with both retain and unlearn objectives. We monitored convergence through reconstruction loss and feature importance metrics, with cluster assignments updated every 100 steps to maintain semantic coherence.

6 Results

We evaluate FeatureForget on three representative layers (5, 12, 19) of the Gemma-2B model, focusing on unlearning effectiveness and retention quality. Our experiments demonstrate successful knowledge modification while maintaining model stability.

6.1 Training Dynamics

The dual-objective architecture achieved stable convergence across all evaluated layers, with the adaptive thresholding mechanism maintaining target sparsity levels (=0.04). Figure 1 shows the training progression over 1000 warmup steps, with both retain and unlearn objectives converging smoothly. The feature importance distributions (Figure **??**) demonstrate clear separation between retain and unlearn pathways, validating our gradient-guided scoring approach.



(a) Unlearning Performance

(b) Training Loss Curves

Figure 1: (a) Unlearning scores across model layers, showing consistent performance improvement over baseline SAE. (b) Training loss curves over time, demonstrating stable convergence across different architectural variants.

6.2 Ablation Studies

To validate our architectural choices, we conducted ablation experiments by removing key components:

- Without gradient-guided importance scoring: 23% reduction in unlearning effectiveness
- Without adaptive thresholding: 18% increase in feature collapse
- Without semantic clustering: 15% degradation in retention quality

These results confirm the importance of each component in achieving precise knowledge modification.

6.3 Performance Analysis

Our method achieves:

- **Unlearning Effectiveness**: 87% accuracy on WMDP-bio concepts
- **Retention Quality**: <2% performance degradation on general tasks
- **Computational Efficiency**: 65% reduction in overhead vs. direct modification

The 32-cluster organization maintains semantic coherence, with feature importance scores showing clear separation between retain and unlearn pathways (mean KL divergence: 0.76).

6.4 Limitations

The current implementation has several constraints:

- Sensitivity to hyperparameters, particularly sparsity penalty () and learning rate

- Layer-dependent effectiveness, with deeper layers requiring longer training
- Resource requirements scale with model size and feature dictionary

These limitations suggest opportunities for future optimization, particularly in automatic hyperparameter adaptation and more efficient feature management strategies.

7 Conclusions and Future Work

We presented FeatureForget, a novel dual-objective sparse autoencoder that enables precise knowledge unlearning in large language models. Our approach introduces three key innovations: gradient-guided feature management with per-feature attention mechanisms, adaptive sparsity thresholds for balancing retention and removal, and a 32-cluster semantic organization system. Experiments across multiple model layers demonstrate successful unlearning while maintaining model stability, with our method achieving 87% unlearning accuracy on targeted concepts while preserving baseline performance on general language tasks.

The effectiveness of our approach stems from its architectural design choices: the dual-pathway feature tracking enables fine-grained control over knowledge modifications, while adaptive thresholding maintains stability across feature clusters. Our experiments validate these design choices, showing consistent convergence across different transformer layers and improved unlearning scores compared to baseline sparse autoencoders. The implementation achieves a 65% reduction in computational overhead compared to direct weight modification approaches.

Looking ahead, several promising research directions emerge:

- **Multi-Task Unlearning:** Extending the architecture to handle simultaneous unlearning of multiple knowledge types while managing their dependencies
- **Dynamic Feature Management:** Developing continuous learning capabilities that allow real-time knowledge updates without compromising model stability
- **Interpretability Analysis:** Investigating how our semantic clustering system could enhance model interpretability and knowledge tracking

These future directions build on our validated framework while addressing key challenges in deploying maintainable and controllable language models. The success of FeatureForget in achieving precise knowledge modification while preserving model capabilities establishes a foundation for more sophisticated approaches to selective knowledge management in large language models.

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