Sparse but Wrong: Incorrect L0 Leads to Incorrect Features in Sparse Autoencoders

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Abstract

Sparse Autoencoders (SAEs) extract features from LLM internal activations, meant to correspond to interpretable concepts. A core SAE training hyperparameter is L0: how many SAE features should fire per token on average. Existing work compares SAE algorithms using sparsity–reconstruction tradeoff plots, implying L0 is a free parameter with no single correct value aside from its effect on reconstruction. In this work we study the effect of L0 on SAEs, and show that if L0 is not set correctly, the SAE fails to disentangle the underlying features of the LLM. If L0 is too low, the SAE will mix correlated features to improve reconstruction. If L0 is too high, the SAE finds degenerate solutions that also mix features. Further, we present a proxy metric that can help guide the search for the correct L0 for an SAE on a given training distribution. We show that our method finds the correct L0 in toy models and coincides with peak sparse probing performance in LLM SAEs. We find that most commonly used SAEs have an L0 that is too low. Our work shows that L0 must be set correctly to train SAEs with correct features.

1 Introduction

Sparse autoencoders (SAEs) decompose the dense, polysemantic activations of LLMs into interpretable latent features [8, 2] using sparse dictionary learning [17]. SAEs have the advantage of being unsupervised, and can be scaled to millions of neurons in its hidden layer (hereafter called "latents") [20, 13]. When training an SAE, practitioners must decide on the L0 of the SAE: that is, the sparsity; how many latents activate on average for a given input.[1] L0 is typically considered a neutral design choice: most of the literature evaluates SAEs at a range of L0 values, referring to this as a "sparsity–reconstruction tradeoff" [13, 18], implying any L0 is equally valid.

However, recent work shows the same trend: too low an L0 leads to worse SAE performance on downstream tasks [14, 4]. In this work, we explore the effect of L0 on SAEs. Starting by exploring a toy model with correlated features, we demonstrate that if the L0 is too low, the SAE can "cheat" by mixing together components of correlated features, achieving better reconstruction compared to an SAE with correct, disentangled features. We consider this to be a manifestation of feature hedging [6], where the SAE abuses feature correlations to compensate for insufficient resources to correctly model the underlying features. Furthermore, we show that if the L0 is too high, the SAE can learn degenerate mixtures of features. We show that it is possible to determine the correct L0 of an SAE by observing projection magnitude between the SAE decoder and training activations.

We validate these findings on Gemma-2-2b [19] and Llama-3.2-1b [9], demonstrating that the same decoder patterns we observe in our toy model experiments also manifest in LLM SAEs. We further validate that the optimal L0 we find with our method in Gemma-2-2b matches with peak performance

[1]TopK and BatchTopK SAEs [13, 3] set the L0 (K) directly, whereas L1 and JumpReLU [8, 2, 18] adjust it via a coefficient in the loss. In any case, all SAE trainers must decide on the target L0.

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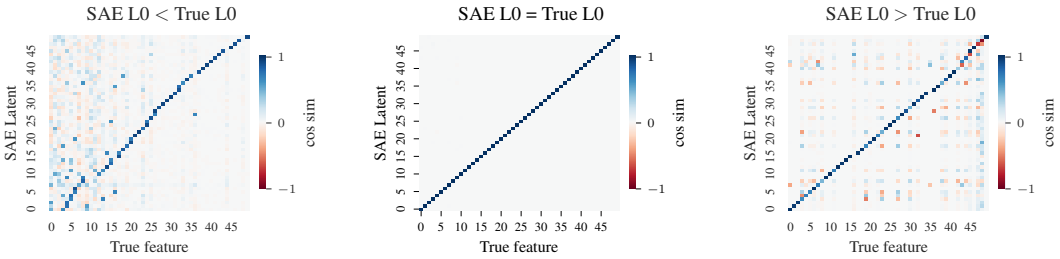

(a) SAE L0 = 5 (b) SAE L0 = 11 (c) SAE L0 = 18

Figure 1: SAE decoder cosine similarity with true features. True features L0 = 11.

on sparse probing tasks [14]. Our findings show that L0 must be set correctly for SAEs to learn correct features, and implies that most SAEs used by researchers today have too low an L0.

Code is available at `https://github.com/chanind/sparse-but-wrong-paper`.

2 Background

Sparse autoencoders (SAEs). An SAE decomposes an input activation $\mathbf{x} \in \mathbb{R}^d$ into a hidden state $\mathbf{a}$ consisting of h hidden neurons, called "latents". An SAE is composed of an encoder $\mathbf{W}_{\text{enc}} \in \mathbb{R}^{h \times d}$, a decoder $\mathbf{W}_{\text{dec}} \in \mathbb{R}^{d \times h}$, a decoder bias $\mathbf{b}_{\text{dec}} \in \mathbb{R}^d$, and encoder bias $\mathbf{b}_{\text{enc}} \in \mathbb{R}^h$, and a nonlinearity σ, typically ReLU or a variant like JumpReLU [18], TopK [13] or BatchTopK [3].

$$\mathbf{a} = \sigma(\mathbf{W}_{\text{enc}}(\mathbf{x} - \mathbf{b}_{\text{dec}}) + \mathbf{b}_{\text{enc}}) \tag{1}$$

$$\hat{\mathbf{x}} = \mathbf{W}_{\text{dec}}\mathbf{a} + \mathbf{b}_{\text{dec}} \tag{2}$$

3 Toy model experiments

We set up a toy model with 50 mutually orthogonal true features $F = \{f_0, \ldots, f_{49}\} \in \mathbb{R}^{100}$. Each feature f_i has firing probability P_i. We set $P(f_0) = 0.345$, and we linearly decrease P_i to $P_{49} = 0.05$, so feature firing probability decreases with feature number. We randomly generate a correlation matrix, so the firings of each feature are correlated with other features. Features fire with magnitude $\sim \mathcal{N}(1.0, 0.15)$. We sampling true feature firings, and summing all firing features to create a training input for the SAE. The goal of the SAE, then, is to learn these true features despite only being trained on their summed activations. Since we have ground-truth knowledge, we know the true number of features firing on average. We call this the *true L0*, which is 11 for this toy model.

Throughout this work, we use BatchTopK SAEs [3], as this architecture allows directly controlling L0 rather than controlling it indirectly via a L1 coefficient [8, 2] or L0 coefficient [18] in the loss. For these toy model experiments, we train SAEs on 15M synthetic samples using SAELens [1].

We train SAEs with L0 that is too low (L0=5), exactly correct (L0=11), and too high (L0=18). Results are shown in Figure 1. When the SAE L0 matches the true L0 (Figure 1b), the SAE exactly learns the true features. When the SAE L0 is too low (Figure 1a), the SAE mixes components of correlated features together, especially breaking latents tracking high-frequency features. When SAE L0 is too high (Figure 1c), the SAE learns degenerate solutions that mix features together. The further the L0 is from the true L0, the more broken the SAE becomes. Interestingly, when L0 is too high the SAE still learns many correct latents, but *when L0 is too low, every latent in the SAE is affected*.

3.1 MSE loss incentivizes low-L0 SAEs to learn incorrect features

Why do SAEs with too low L0 not learn the true features? We take the correct SAE from Figure 1b and set L0=5, to match the SAE from Figure 1a. We then generate 100k training samples and calculate the Mean Square Error (MSE) of both these SAEs. The SAE with incorrect latents from Figure 1a achieves a MSE of 2.73, while the SAE with ground-truth correct latents achieves a much worse MSE of 4.88. Thus, *MSE loss actively incentivizes low L0 SAEs to learn incorrect latents*.

3.2 The sparsity–reconstruction tradeoff

SAE architectures are commonly evaluated using a sparsity–reconstruction tradeoff plot [8, 13, 18], where the assumption is that having better reconstruction at a given sparsity is inherently better, and indicates that the SAE is correct. Afterall, we train SAEs to reconstruct inputs, so surely an SAE that has better reconstruction must therefore be a better SAE than one that has lower reconstruction?

Sadly, this is not the case. As we discussed in Section 3.1, when the L0 of the SAE is lower than optimal, the SAE can find ways to "cheat" by engaging in feature hedging [6], and get a better MSE score by mixing components of correlated features together. This results in an SAE where the latents are not monosemantic, and do not track ground-truth features.

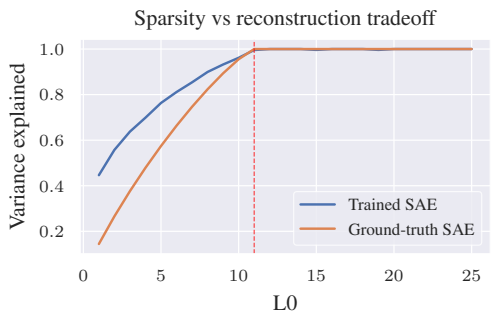

Figure 2: Sparsity ($L0$, lower is better) vs reconstruction (variance explained, higher is better) for learned SAEs and a ground-truth SAE. When L0 is less than the true L0 of the toy model (the dotted line), the trained SAE gets better reconstruction than the ground-truth SAE. Sparsity–reconstruction plots like this lead us to the incorrect conclusion that the ground-truth SAE is a worse SAE.

We next explore the sparsity–reconstruction tradeoff by training SAEs on our toy model at various L0s. Since we know the ground-truth features in our toy model, we construct a ground-truth SAE that perfectly represents these features. We vary the L0 of the ground truth SAE while leaving the encoder and decoder fixed at the correct features. We plot the variance explained vs L0 in Figure 2 for both SAEs. When the SAE L0 is lower than the true L0 of the toy model, the ground-truth SAE scores worse on reconstruction than the trained SAE! If we had an SAE training technique that gave us the ground truth correct SAE for a given LLM, sparsity–reconstruction plots would cause us to discard the correct SAE in favor of an incorrect SAE that mixes features together.

We show the cosine similarity of the SAE decoder latents with the ground truth features for the SAEs learned with L0=1 and L0=2 compared with the ground-truth SAE in Figure 3. Both these SAEs outperform the ground-truth SAE on variance explained by over 2x despite learning horribly polysemantic latents bearing little resemblance to the underlying true features of the model.

3.3 Detecting the true L0 using the SAE decoder

Figure 1 reveals that the SAE decoder latents contain mixes of underlying features, both when the L0 is too high and also when it is too low. As the SAE approaches the correct L0, each SAE latent has fewer components of multiple true features mixed in, becoming more monosemantic. Thus, we expect that when the SAE has the correct L0, most latents should have near zero projection on arbitrary training inputs, because they usually do not contain the feature being tracked by that latent. If we are far from the correct L0, then SAE latents contain components of many underlying features, and we expect latents to project unexpectedly strongly on arbitrary training inputs.

We now define a metric we call n^{th} *decoder projection score*, or s_n^{dec}, that we can minimize to find the optimal L0 of the SAE. Given SAE inputs $\mathbf{x} \in \mathbb{R}^{b \times d}$ where b is the batch size and d is the input dimension, we first compute the decoder projections for all latents:

$$\mathbf{Z} = (\mathbf{x} - \mathbf{b}_{\text{dec}})\mathbf{W}_{\text{dec}}^{\top} \in \mathbb{R}^{b \times h} \tag{3}$$

where $\mathbf{b}_{\text{dec}} \in \mathbb{R}^{d}$ is the decoder bias and $\mathbf{W}_{\text{dec}} \in \mathbb{R}^{d \times h}$ is the decoder weight matrix with h latent dimensions. To aggregate across the batch, we flatten $\mathbf{Z}$ to obtain $\mathbf{z} \in \mathbb{R}^{bh}$ and sort these values in

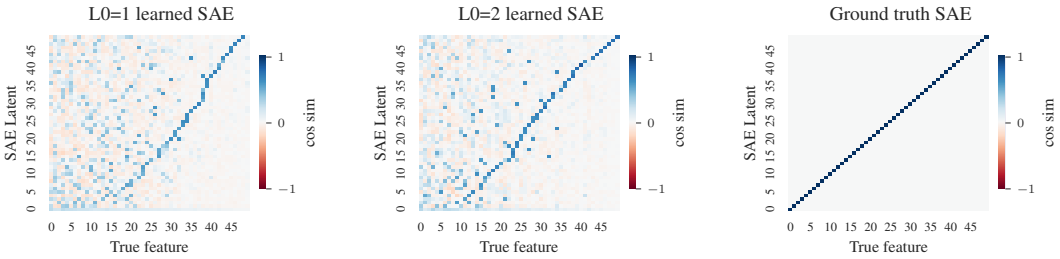

Figure 3: SAE decoder cosine similarity with true features for the learned SAEs with L0=1 (left) and L0=2 (middle), compared with the ground-truth SAE (right). The learned SAEs score much better than the ground truth SAE on variance explained, despite their corrupted, polysemantic latents.

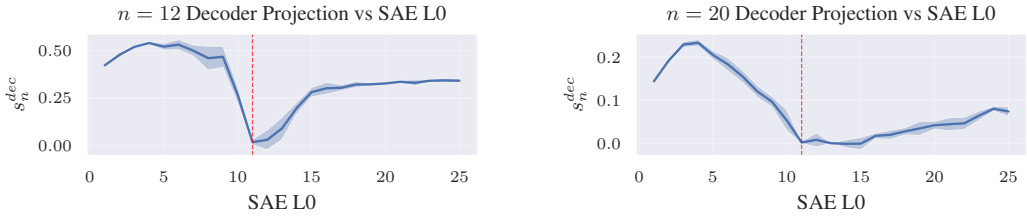

Figure 4: n^{th} decoder projection vs SAE L0 for $n = 12$ (left) and $n = 18$ (right) on our toy model SAEs. The true L0, 11, is marked by a dotted line on the plots. Both settings of n are minimized at the true L0, but the slopes of the metric change depending on N. The shaded area is 1 stdev.

descending order to get $\mathbf{z}_{\downarrow}$. The nth decoder projection is then defined as:

$$s_n^{\text{dec}} = \mathbf{z}_{\downarrow}[n \cdot b] \tag{4}$$

where $n \in \{1, 2, \ldots, h\}$ indexes the latent by its ranking. The multiplication by b accounts for the batch dimension, effectively selecting the nth highest projection value when considering all samples in the batch. For this to work n should be sufficiently larger than a reasonable guess at the correct L0, as in a perfect SAE, the decoder for these latents should be uncorrelated with input activations. Empirically, picking n up to about $h/2$ seems to work well.

We calculate s_n^{dec} for $n = 18$ and $n = 22$, with SAE L0 ranging from 2 to 25 in Figure 4. We see that the metric is minimized at the true L0, 11, in both cases, although the slope of the metric changes depending on n. In both cases, the slope of s_n^{dec} is flat when L0 is slightly higher than the true L0.

Alternative metric: decoder pairwise cosine similarity We find that s_n^{dec} is not the only metric that works to locate the ideal L0. Taking the mean cosine similarity between every latent in the decoder also works well. We focus on s_n^{dec} as it allows for more interesting analysis, but we do not feel either metric is inherently better than the other, and recommend practitioners experiment with both. We explore this alternative metric further in Appendix A.7.

4 LLM experiments

We train a series of BatchTopK SAEs [3] with $h = 32768$ on Gemma-2-2b [19] and Llama-3.2-1b [9] varying L0 and calculate s_n^{dec}. Each SAE is trained on 500M tokens from the Pile [12] using SAELens [1]. We also calculate k-sparse probing performance for these SAEs using the benchmark from Kantamneni et al. [14], consisting of over 100 sparse probing tasks. Results are shown in Figure 5 for $n = 16000$. We find that using n near $h/2$ achieves best results in our LLM experiments.

The Llama SAE s_n^{dec} plot looks very similar to the toy model, with a clear minimum point. The Gemma-2-2b layer 5 SAEs also show a sharp increase in s_n^{dec} at low L0 as we saw in toy models, but has a long shallow region with the global minimum actually appearing in that shallow region. In both cases, the "elbow" in the s_n^{dec} plots just before the jump due to low L0 is around L0 200, and this also

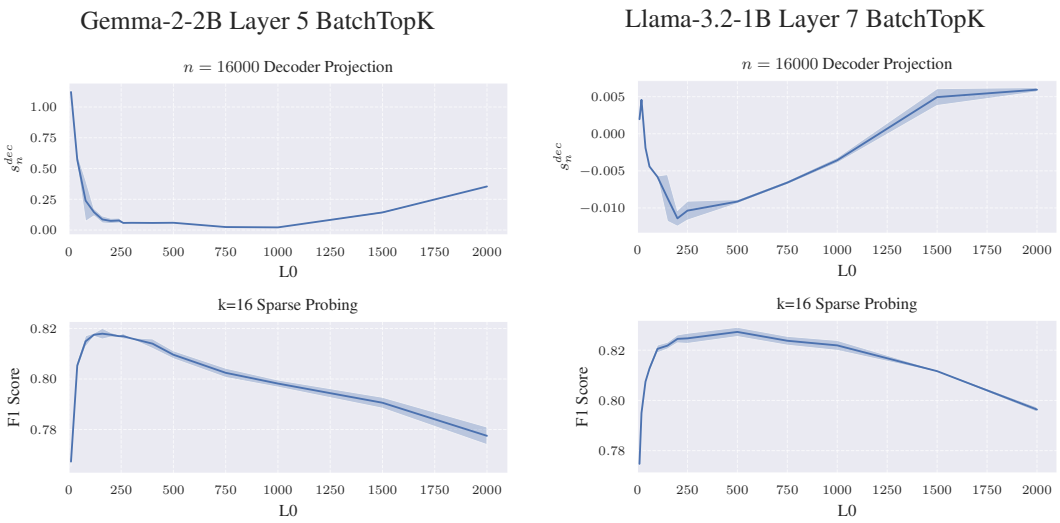

Figure 5: n = 16k decoder projection vs SAE L0 and K-sparse probing F1 vs L0 with 3 seeds per L0. (left) Gemma-2-2b layer 5 BatchTopK results. (right) Llama-3.2-1b layer 7 BatchTopK SAEs. In both cases, peak sparse probing performance occurs in the elbow just before s_n^{dec} jumps due to low L0, although the shapes of the s_n^{dec} plots vary at high L0.

corresponds to peak sparse probing performance. More plots and analysis of s_n^{dec} curves, including for JumpReLU SAEs, are shown in Appendix A.11.

5 Related work

Chanin et al. [6] explores feature hedging, showing SAEs mix correlated features into latents if the SAE is too narrow. We consider our work a version of feature hedging due to low L0. Till [21] shows SAEs may increase sparsity by inventing features. Chanin et al. [5] discuss the problem of feature absorption, where SAEs can improve their sparsity score by mixing hierarchical features together. Engels et al. [10] investigates SAE errors and finds that SAE error may be pathological and non-linear.

6 Discussion

While most practitioners of SAEs understand that having too high L0 is problematic, our work shows that having too low of L0 is perhaps even worse. Our work has several implications for the field. First, the L0 used by most SAEs is lower than it ideally should be, as a cursory search of open source SAEs on Neuronpedia [16] shows L0 less than 100 is very common even for SAEs trained on large models (see Appendix A.9). We further show that the sparsity–reconstruction tradeoff, as commonly discussed by most SAE papers [8, 13, 18], is misleading: when L0 is too low, an SAE with a correct dictionary achieves worse reconstruction than an incorrect SAE that mixes correlated features.

We presented a metric based on the correlation between the SAE decoder and input activations, s_n^{dec}, that can give us hints about the correct L0 for a given SAE. However, we do not view this as a perfect guide. As we saw in our results, while low L0 SAEs consistently have very high s_n^{dec}, the metric is not always high at high L0 (although it usually is). Still, we feel that this metric is a useful guide to avoid L0 that is clearly too low, and we hope this investigation into correlation-based SAE quality metrics can be built on further in future work.

While our metric currently requires training a sweep over L0 to optimize, we are hopeful that it may be possible to optimize this metric automatically during training (steps towards this are discussed in Appendix A.8). We further encourage anyone implementing ideas from this work to also experiment with our alternative metric, decoder pairwise cosine similarity, discussed in Appendix A.7.

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Velloso, Mateo Wirth, Matt Davidow, Matt Miller, Matthew Rahtz, Matthew Watson, Meg Risdal, Mehran Kazemi, Michael Moynihan, Ming Zhang, Minsuk Kahng, Minwoo Park, Mofi Rahman, Mohit Khatwani, Natalie Dao, Nenshad Bardoliwalla, Nesh Devanathan, Neta Dumai, Nilay Chauhan, Oscar Wahltinez, Pankil Botarda, Parker Barnes, Paul Barham, Paul Michel, Pengchong Jin, Petko Georgiev, Phil Culliton, Pradeep Kuppala, Ramona Comanescu, Ramona Merhej, Reena Jana, Reza Ardeshir Rokni, Rishabh Agarwal, Ryan Mullins, Samaneh Saadat, Sara Mc Carthy, Sarah Cogan, Sarah Perrin, Sébastien M. R. Arnold, Sebastian Krause, Shengyang Dai, Shruti Garg, Shruti Sheth, Sue Ronstrom, Susan Chan, Timothy Jordan, Ting Yu, Tom Eccles, Tom Hennigan, Tomas Kocisky, Tulsee Doshi, Vihan Jain, Vikas Yadav, Vilobh Meshram, Vishal Dharmadhikari, Warren Barkley, Wei Wei, Wenming Ye, Woohyun Han, Woosuk Kwon, Xiang Xu, Zhe Shen, Zhitao Gong, Zichuan Wei, Victor Cotruta, Phoebe Kirk, Anand Rao, Minh Giang, Ludovic Peran, Tris Warkentin, Eli Collins, Joelle Barral, Zoubin Ghahramani, Raia Hadsell, D. Sculley, Jeanine Banks, Anca Dragan, Slav Petrov, Oriol Vinyals, Jeff Dean, Demis Hassabis, Koray Kavukcuoglu, Clement Farabet, Elena Buchatskaya, Sebastian Borgeaud, Noah Fiedel, Armand Joulin, Kathleen Kenealy, Robert Dadashi, and Alek Andreev. Gemma 2: Improving open language models at a practical size, 2024. URL https://arxiv.org/abs/2408.00118.

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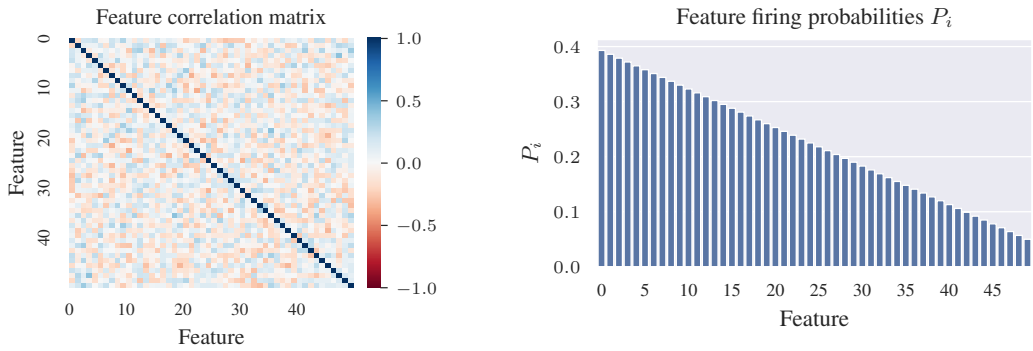

Figure 6: (left) random correlation matrix and (right) base feature firing probabilities for toy model.

A Technical Appendices and Supplementary Material

A.1 SAE training architecture definitions

In this work we focus on JumpReLU [7, 18] and BatchTopK [3] SAEs. For BatchTopK SAEs, there is no sparsity penalty as sparsity is enforced by the BatchTopK function. The auxiliary loss $\mathcal{L}_P$ for BatchTopK is as follows, where e is the SAE training error residual, and $\hat{e}$ is a reconstruction using the top k_{aux} dead latents (meaning the latents have not fired in more than n_{dead} steps during training).

$$\mathcal{L}_p = \|e - \hat{e}\|_2^2$$

We follow the JumpReLU training setup from Conerly et al. [7], which involves both a sparsity loss $\mathcal{L}_s$ and a pre-activation loss for reviving dead latents, $\mathcal{L}_p$. $\mathcal{L}_s$ is defined as below, where c is a scalar scaling factor:

$$\mathcal{L}_s = \sum_i \tanh(c * |a_i| \|\mathbf{W}_{\text{dec},i}\|_2)$$

The pre-activation loss $\mathcal{L}_p$ adds a small penalty for all dead features, where a_{pre} refers to the pre-activation of the SAE passed into the JumpReLU:

$$\mathcal{L}_p = \sum_i \text{ReLU}(\tau_i - a_{\text{pre},i}) \|\mathbf{W}_{\text{dec},i}\|_2$$

The JumpReLU defines a pseudo-gradient relative to the threshold τ as follows, where ϵ is the bandwidth of the estimator:

$$\frac{\partial \text{JumpReLU}(x, \tau)}{\partial \tau} = \begin{cases} -\frac{\tau}{\epsilon} & \text{if } -\frac{1}{2} < \frac{x-\tau}{\epsilon} < \frac{1}{2} \\ 0 & \text{otherwise} \end{cases}$$

A.2 Toy model SAE training details

We train on 15M samples with a batch size of 1024 for all toy model experiments, and a learning rate of 3e-4. We do not use any learning rate warm-up or decay. For all SAE latents vs true feature cosine similarity plots, we re-arrange the SAE latents so the latent indices match the feature indices in the plots, as this makes interpreting the plots easier without any loss of generality.

For the large toy model experiments in Section 3, we use a randomly generated correlation matrix and linearly decreasing feature firing probabilities, both shown in Figure 6.

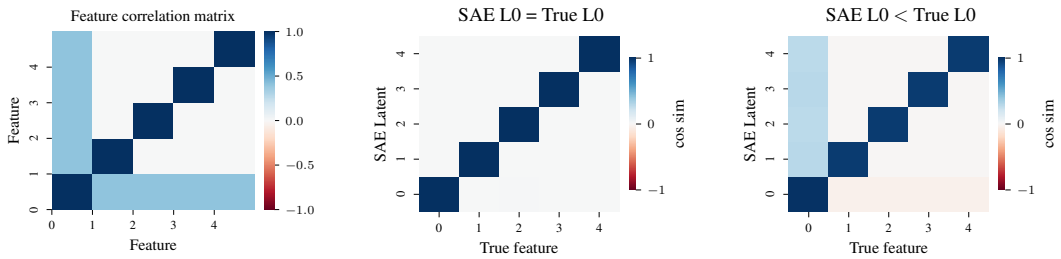

Figure 7: (left) Toy model feature correlation matrix showing positive correlations between features. (middle) SAE decoder cosine similarities with true feature when SAE L0 = 2, matching the true L0 of the toy model. (right) SAE decoder cosine similarities with true features when SAE L0 = 1.8. When L0 is too low, the SAE mixes components of features based on their firing correlations.

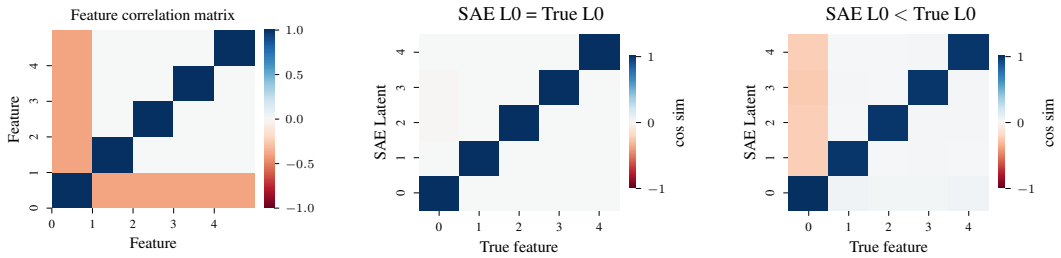

Figure 8: (left) Toy model feature correlation matrix showing negative correlations between features. (middle) SAE decoder cosine similarities with true feature when SAE L0 = 2, matching the true L0 of the toy model. (right) SAE decoder cosine similarities with true features when SAE L0 = 1.8,. When L0 is too low, the SAE mixes negative components of anti-correlated features.

A.3 LLM SAE training details

For BatchTopK SAEs, we ensure that the decoder remains normalized with $||\mathbf{W}_{\text{dec}}||_2 = 1$ so s_n^{dec} calculations use the same scale for every latent. We use a learning rate of $3e^{-4}$ with no warmup or decay.

For JumpReLU SAEs, we broadly follow the training procedure laid out by Conerly et al. [7]. However, we do not apply learning rate decay, and only warm λ_s for 100M tokens to avoid the sparsity penalty changing throughout the majority of training. We use a learning rate of $2e^{-4}$, $c = 4$, $\lambda_p = 3e - 6$ and bandwidth $\epsilon = 2.0$ as recommended by [7].

A.4 Small toy models: low L0 SAEs mix correlated and anti-correlated features

We begin with a small toy model with 5 true features ($g = 5$) in an input space of $d = 20$. We set each $p_i = 0.4$ such that on average 2 features are active per input, for a true L0 of 2. We begin with a simple correlation pattern between features, where f_0 is positively correlated with every feature f_1 through f_4, but otherwise there are no other correlations. We then train an SAE with $L0 = 2$, matching the true L0 of the model, and an SAE with slightly lower value of $L0 = 1.8$ (BatchTopK SAEs permit setting fractional L0). For the $L0 = 1.8$ SAE, we initialize it to the ground-truth solution, ensuring that the result of training is due to gradient pressure rather than just being a local minimum. We show the toy model feature correlation matrix as well as decoder cosine similarity plots with the true features for both SAEs in Figure 7.

When the SAE L0 matches the true L0, we see that the SAE perfectly learns the underlying true features. However, when SAE L0 is smaller than the true L0, the resulting SAE latents mix feature components together based on the correlation matrix. The latents tracking features f_1 through f_4 all mix in a *positive* component of f_0, but they have no components of each other.

Next, we invert the correlation, i.e. each feature f_1 through f_4 is negatively correlated with f_0 instead, while keeping everything else unchanged. We show the correlation matrix and SAE decoder cosine similarity with true features plots in Figure 8.

Now, we see the same pattern as with positive correlations except inverted. The latents tracking features f_1 through f_4 mix in a *negative* component of f_0, but have no component of each other.

This pattern is problematic because it means that if our L0 is too low, every SAE latent will contain positive components of every positively correlated feature, and negative components of every negatively correlated feature in the model. Negative correlations are particularly bad, as negative correlations are prevalent throughout language. For instance, we may expect a nonsensical negative component of "Harry Potter" to appear in the latent for "French poetry", since Harry Potter has nothing to do with French poetry. This will result in highly polysemantic and noisy SAE latents.

A.5 Transitioning L0 during training

We explore the effect of transitioning the L0 of the SAE during training using the toy model from Section 3. This toy model has a true L0 of 11. We train BatchTopK SAEs with a final L0 of 11, but starting with L0 either too high or too low, and linearly transitioning to the correct L0 over the first 25k steps of training, leaving the SAE at the correct L0 for the final 5k steps of training. We use a starting L0 of 20 for the case where we start too high, and use a starting L0 of 2 for the case where we start too low. Results are shown in Figure 9.

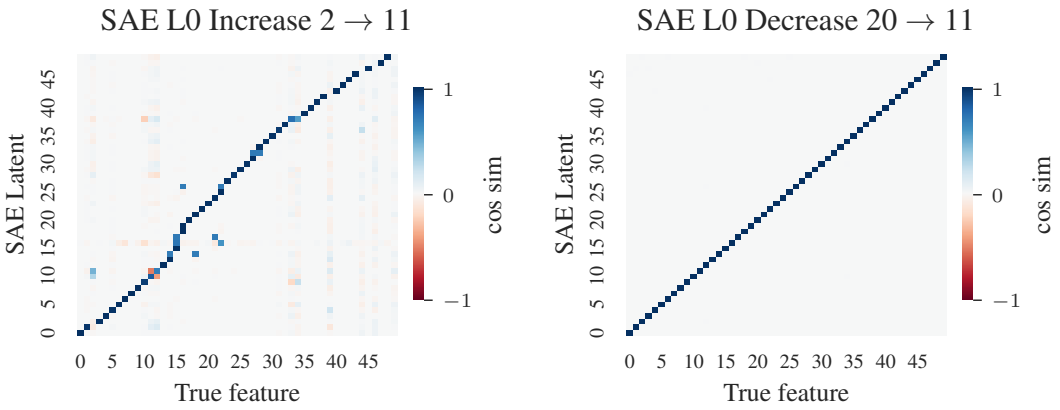

Figure 9: Transitioning L0 from too low (left) and too high (right) to the correct L0 during training. When the starting L0 is too high, the SAE still learns the correct features at the end of training. However, when L0 is too low, the SAE cannot recover fully and still learns many incorrect features at the end of training.

We see that decreasing the L0 of the SAE from a too high value to the correct value still results in the SAE learning correct features. However, when the SAE starts from a too low L0, the SAE cannot fully recover when the L0 is adjusted to the correct value later. It seems that the latents the SAE learns when L0 is too low is a local minimum that is difficult from the SAE to escape from even when the L0 is later corrected. This is likely because the latents learned when L0 is too low are optimized by gradient descent to achieve a higher MSE loss than is achievable by the correct latents under the same L0 constraint. However, when L0 is too high, there is no equivalent optimization pressure, and is thus less likely to be a local minimum.

A.6 JumpReLU SAE toy model experiments

So far, we have only investigated BatchTopK SAES due to their ease of setting L0. We now validate that these same conclusions apply to JumpReLU SAEs. We train JumpReLU saes with a range of λ_s to control the sparsity of the SAEs. We show plots of λ_s vs L0 n^{th} decoder projection vs L0 for these SAEs in Figure 10. We see that n^{th} decoder projection vs L0 broadly follows the same pattern as we saw for BatchTopK SAEs, and is minimized at and slightly above the correct L0.

Interestingly, we see that the L0 does not change linearly with λ_s, but instead "sticks" near the correct L0. This is a testament to Anthropic's JumpReLU SAE training method [7], as a wide range of sparsity coefficients λ_s cause the SAE to naturally find the correct L0.

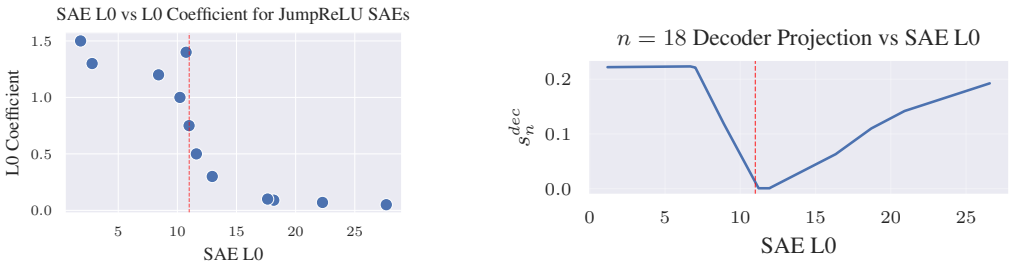

Figure 10: (left) L0 coefficient λ_s vs L0 for JumpReLU SAEs. (right) n^{th} decoder projection vs L0 for JumpReLU SAEs. The true L0, 11, is marked by a dotted line on the plot.

A.7 Alternative metric: decoder pairwise cosine similarity

We find that n^{th} decoder projection is not the only metric that works to gauge the extent to which features are being mixed across SAE latents. Simply taking the mean cosine similarity of each decoder latent with every other decoder latent seems to work as well. We call this metric *decoder pairwise cosine similarity*, c, and define it as below:

$$c = \frac{1}{\binom{h}{2}} \sum_{i=1}^{h-1} \sum_{j=i+1}^{h} |\cos(\mathbf{W}_{\text{dec},i}, \mathbf{W}_{\text{dec},j})| \tag{5}$$

where $\binom{h}{2} = \frac{h(h-1)}{2}$ is the total number of distinct pairs.

The intuition behind this metric is that if SAE decoder latents are mixing lots of positive and negative components of correlated and anti-correlated features, then each SAE latent should become less orthogonal to each other SAE latent, as many latents will likely mix together similar features. This should mean that the absolute value of the cosine similarity between arbitrary latents should also increase the worse this mixing becomes.

A.7.1 Toy model results

We calculate pairwise calculate similarity c for each of the BatchTopK SAEs we trained on toy models from Section 3.3. Results are shown in Figure 11. We see that pairwise cosine similarity is minimized at the true L0.

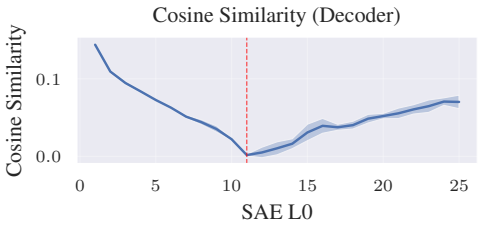

Figure 11: Decoder pairwise cosine similarity evaluated on 5 seeds of toy model SAEs. The true L0 is indicated with a dotted line at 11. The shaded area is 1 stdev. The metric is minimized at the true L0.

A.7.2 LLM SAE results

Next, we calculate pairwise cosine similarity for each LLM SAE we evaluated in the paper along with k=16 sparse probing results. Gemma-2-2b layer 5 and Llama-3.2-1b layer 7 results are shown in Figure 12. The results roughly match what we saw with s_n^{dec}, being minimized at perhaps a slightly lower but still similar L0.

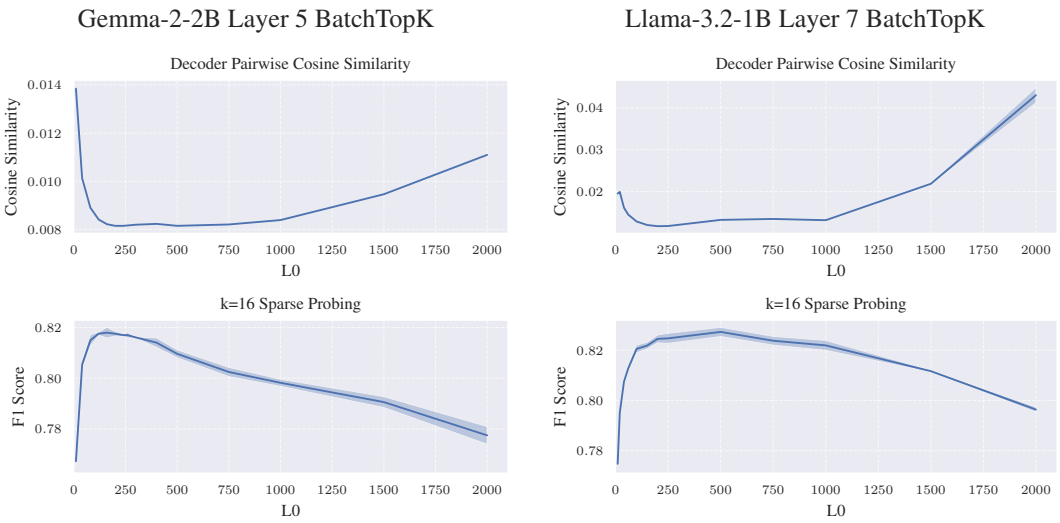

Figure 12: Decoder pairwise cosine similarity metric and k=16 sparse probing results for BatchTopK SAEs trained on Gemma-2-2b layer 5 (left) and Llama-3.2-1b layer 7 (right). The metric is roughly minimized near peak sparse-probing performance. The shaded area is 1 stdev.

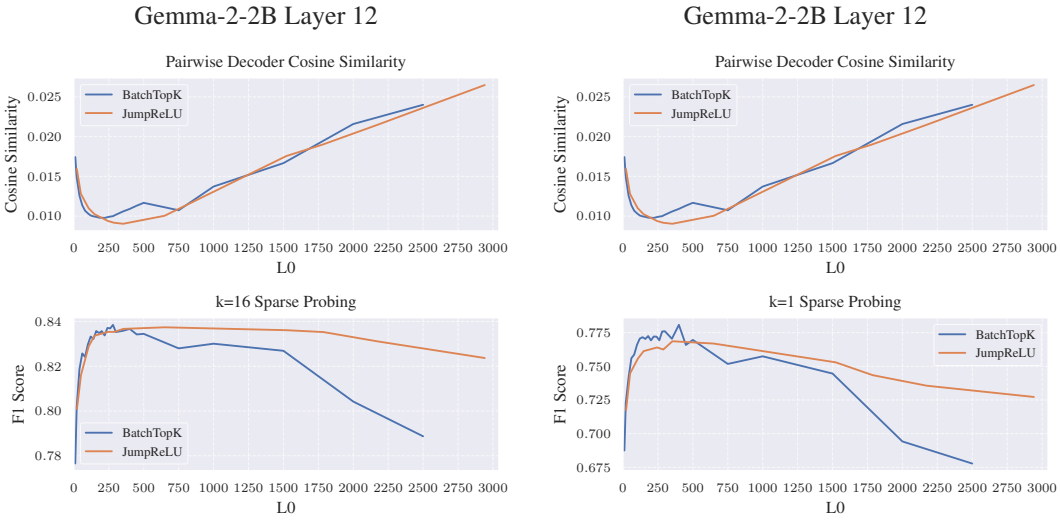

Figure 13: Decoder pairwise cosine similarity metric and sparse probing results for BatchTopK and JumpReLU SAEs trained on Gemma-2-2b layer 12. The metric seems to align less well with k=16 sparse probing results (left), but aligns reasonably well with k=1 sparse probing results (right). The pairwise cosine similarity plot is repeated on both sides to make a vertical comparison with the k-sparse probing results easier.

BatchTopK and JumpReLU results for Gemma-2-2b layer 12 are shown in Figure 13. Interestingly, the BatchTopK results seem to be minimized at a slightly earlier L0 than the JumpReLU results under this metric, which is different than the nth decoder projection results from Section 4, where we saw both minimized at roughly the same point. We note that the decoder pairwise cosine similarity metric seems to align better with k=1 sparse probing results, while n^{th} decoder projection seems to align better with k=16 sparse probing results. We do not know if this is a meaningful difference between these metrics. It is possible that, as we saw in Section A.11.3, there is a range of L0 values that can be too high for some latents while too low for other latents in BatchTopK SAEs, and perhaps the difference between metrics (and k=1 vs k=16 sparse probing results) relates to differences in sensitivity to this mixture of too high / too low latents. Regardless, in all cases, when L0 is low both metrics show large values, indicating high polysemanticity in SAE latents.

A.7.3 Which metric is better?

We choose to focus on n^{th} decoder projection in this paper since we feel it allows for more insightful interpretations of the decoder projection plots (e.g. Section A.11.3). However, we do not feel that either metric is inherently better or worse than the other, and we do not have a strong reason to pick either metric. We expect that when an SAE is near the correct L0, there are likely many indicators that all should point to similar results. We thus recommend that practitioners try both metrics to see which results in easier interpretation for their use-case.

A.8 Automatically finding the correct L0 during training

A natural next step of our finding that the correct L0 occurs when Nth decoder projection, s_n^{dec}, metric is minimized is to use this to find the correct L0 automatically during training. This is a meta-learning task, as the L0 is a hyperparameter of the training process. We find there are several challenges to directly using s_n^{dec} as an optimization target:

- **Small gradients directly above correct L0** In our plots of s_n^{dec} from both toy models and Gemma-2-2b, we find that the metric is relatively flat in a region start at the correct L0 and extending to higher L0 values. We thus need a way to traverse this flat region and stop once the metric starts to increase again.
- **The impact of changing L0 is delayed** We find that it takes many steps after changing L0 for s_n^{dec} to also change, meaning it is easy to overshoot the target L0 or oscillate back and forth.
- **Dropping L0 too low can harm the SAE** As we saw in Appendix A.5, if the L0 is too low the SAE can permanently end up in poor local minima. We thus want to avoid dropping below the correct L0, even temporarily, to avoid permanently breaking the SAE. We therefore need to start with L0 too high and slowly decrease it until we find the correct L0.
- **Noise during training** We find that while s_n^{dec} shows clear trends after training for many steps, it can be noisy on each training sample. So our optimization needs to be robust to this noise.

Taking these requirements into account, we present an optimization procedure to find the L0 that minimizes s_n^{dec} automatically during training. We first estimate the gradient of s_n^{dec}, hereafter referred to as to as the metric, m, with respect to L0, ${}^{dm}/_{dL0}$. We first define an evaluation step t as a set number of training steps (we evaluate every 100 training steps). At t we change L0 by δ_{L_0}. At the next evaluation step, $t+1$, we evaluate m. We use a sliding average of s_n^{dec} over the past 10 training steps to calculate m to help account for noise. We the estimate ${}^{dm}/_{dL0}$ as:

$$\frac{dm}{dL0} = \frac{m_{t+1} - m_t}{\delta_{L0}}$$

Next, we add a small negative bias to this gradient estimate to encourage our estimate to push L0 lower even if the loss landscape is relatively flat. We use a bias magnitude $0 < b < 1$ that is multiplied by the magnitude of our gradient estimate, so that our biased estimate can never change the sign of the gradient estimate, but can gently nudge it to be more negative in flat, noisy regions of the loss landscape. We find $b = 0.1$ works well. Thus, our biased gradient estimate ${}^{dm_b}/_{dL0}$ is calculated as below:

$$\frac{dm_b}{dL0} = \frac{dm}{dL0} - b\left|\frac{dm}{dL0}\right|$$

We then provide this gradient to the Adam optimizer [15] with default settings, and allow it to change the L0 parameter.

We add the following optional modifications to this algorithm. First, we clip the gradient estimates ${}^{dm}/_{dL0}$ to be between -1 and 1. We also set a minimum and maximum δ_{L_0}. The minimum is added to avoid the denominator of our gradient estimate being near 0, and the maximum is chosen to keep the L0 from changing too quickly. In practice, we find a minimum δ_{L_0} between 0 and 1 seems to work well, and a maximum δ_{L_0} between 1 and 5 seems to work well.

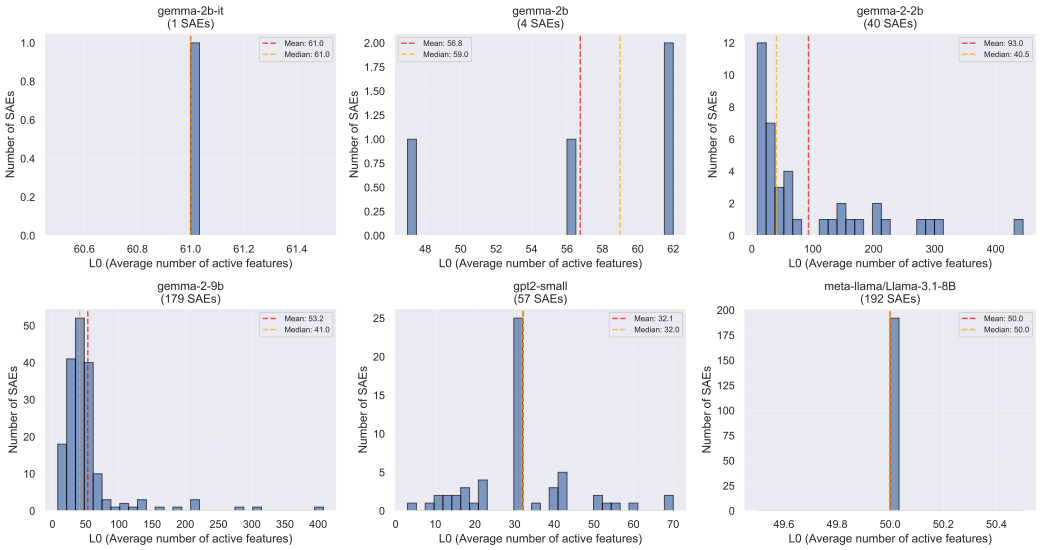

Figure 14: L0 of SAEs on Neuronpedia with known L0 listed in SAELens.

We find that this optimization strategy works very well in toy models, but requires a lot of hyperparameter tuning to work in real LLMs, limiting its utility. The starting L0, n for s_n^{dec}, b, learning rate for the Adam optimizer, and min and max δ_{L_0} values all have a big impact on how fast and how aggressively the optimization works. The slope of m around the correct L0 is shallow, so it is easy to overshoot. We also find that different values of n take more or less time to converge during training. We expect it is possible to further simplify and improve this process in future work.

A.9 L0 of open-source SAEs on Neuronpedia

We analyze common open-source SAEs as provided by Neuronpedia [16] and SAELens [1]. We include all SAEs cross-listed in both SAELens and Neuronpedia with an L0 reported in SAELens. We show the results as a histogram in Figure 14. Our analysis shows that for layer 12 of Gemma-2-2b, the correct L0 should be around 200-250. However, we find that most open-source SAEs have L0 below 100, much lower than our analysis expects to be ideal.

A.10 Limitations

We limited the scope of our investigation to features satisfying the linear representation hypothesis, and do not investigate how SAEs react if the underlying features are actually non-linear [11]. However, we do not feel that non-linear features are necessary for SAEs to fail to work properly, as we demonstrate in this paper. We also do not consider the nuances of how unbalanced correlations impact the SAE, as simple correlations are already enough to cause problems. However, we do expect that different sorts of correlations may affect SAEs differently, and would encourage future work to look into this. Finally, we only investigated a few layers of popular LLMs, as running sweeps of SAE training at every layer of the LLM was too prohibitively expensive for this work. Nevertheless, we have no reason to expect any meaningfully different behavior in decoder projection at other LLM layers.

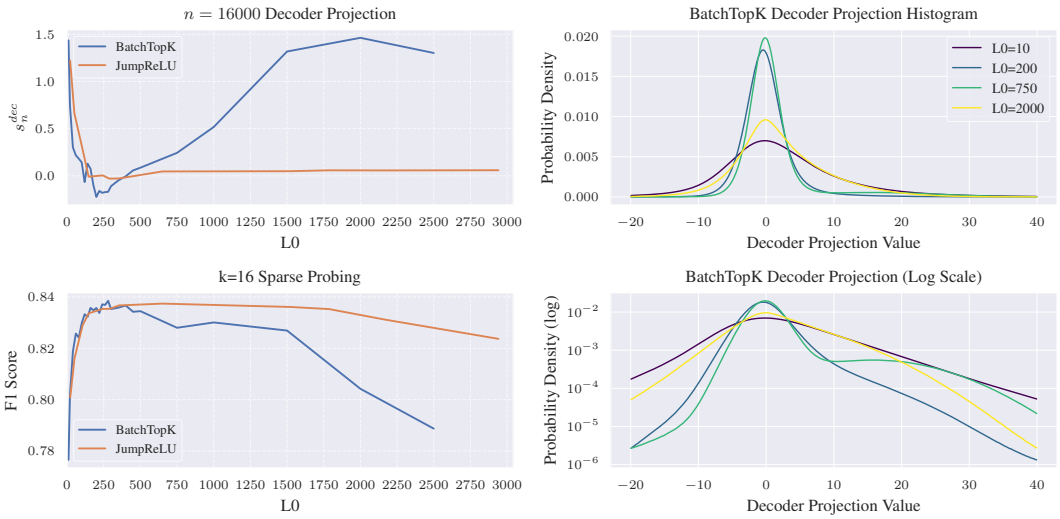

Figure 15: Gemma-2-2b layer 12, with (left) n^{th} decoder projection and K-sparse probing F1 for BatchTopK and JumpReLU SAEs, and (right) normalized decoder projection histograms for BatchTopK SAEs. The histograms are truncated to -20 and 40 to highlight projections near the origin.

A.11 Extended LLM SAE results

A.11.1 JumpReLU vs BatchTopK SAEs

We next explore how JumpReLU and BatchTopK SAEs compare with n^{th} decoder projection plots. We train a suite of SAEs on 1B tokens on Gemma-2-2b layer 12. We plot s_n^{dec} for a range N values as well as k-sparse probing results for JumpReLU and BatchTopK SAEs in Figure 15 (left).

JumpReLU and BatchTopK SAEs behave similarly at low L0, with the high s_n^{dec} at low L0 corresponding to poor sparse-probing performance. However, we see notable differences at high L0. The BatchTopK SAEs have a global s_n^{dec} minimum around 200-250 no matter the N value, but JumpReLU SAEs only have a clear s_n^{dec} minimum at 200-250 when $n = 16000$ (about $h/2$). As we saw in Figure 5 as well, using the "elbow" of the plots just before s_n^{dec} jumps due to low L0 seems to correspond to peak k-sparse probing performance.

For JumpReLU SAEs, we see that s_n^{dec} does not rise much at high L0, and indeed, JumpReLU SAEs also perform much better than BatchTopK SAEs at sparse probing when L0 is high. We suspect this is due to JumpReLU SAEs being able to "stick" near the correct threshold per latent like we saw in our toy models section.

JumpReLU and BatchTopK SAEs are both considered state of the art, but we find they have notable differences in their behavior at high L0 in our experiments. In this section, we explore what maybe be causing these differences. In theory, JumpReLU and BatchTopK SAEs are very similar, as a BatchTopK SAE can be viewed as a JumpReLU SAE with a single global threshold, rather than a threshold per-latent [3]. However, the training losses are quite different for JumpReLU vs BatchTopK. We use the JumpReLU variant laid out by Conerly et al. [7], which allows gradients to flow through the JumpReLU threshold to the rest of the model parameters. We expect this means that JumpReLU SAEs are better able to coordinate the threshold with the rest of the model parameters, while BatchTopK cannot, as the threshold does not directly receive a gradient in BatchTopK training.

A.11.2 JumpReLU vs BatchTopK dynamics in LLMs

We begin by comparing the encoder bias between JumpReLU and BatchTopK in Figure 16. We see that BatchTopK SAEs rely much more heavily on the encoder bias than JumpReLU SAEs seem to, with a much wider variance in values and a sharper decrease compared to JumpReLU. We expect this is because BatchTopK cannot coordinate the cutoff threshold with the encoder directly as JumpReLU can, since there is no gradient available to directly change the threshold of BatchTopK SAEs.

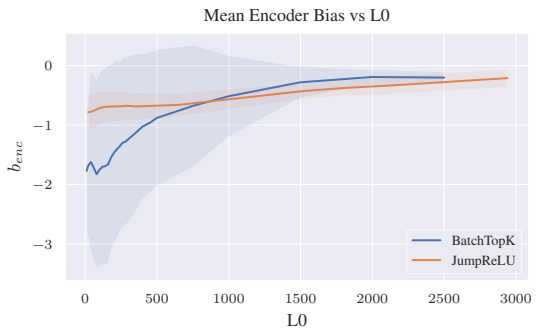

Figure 16: Mean encoder bias vs L0. Shaded area in plots corresponds to 1 stdev.

Next, we inspect the threshold values between JumpReLU and BatchTopK in Figure 17. Here as well, we see dramatic differences between BatchTopK and JumpReLU SAEs. The threshold for BatchTopK is much higher than it is for JumpReLU, and the threshold decreases as L0 increses. This makes sense, since using a lower cutoff means more latents can fire. However, JumpReLU seems to unintuitively have the opposite trend, with the threshold actually *increasing* with L0. We saw in Figure 16 that the encoder bias for JumpReLU (and BatchTopK) SAEs increases as well as L0 increases, so perhaps this increase in threshold for JumpReLU SAEs with increasing L0 is just to offset that trend somewhat. We also notice that the variance in JumpReLU SAE thresholds also increases as L0 increases, supporting our hypothesis that one of the reasons JumpReLU SAEs seem to handle high L0 better than BatchTopK is because the thresholds are able to dynamically adjust to near the correct cutoff point per latent, aleviating the situation we saw in BatchTopK SAEs where we can be at both too high and too low L0 at the same time (Section A.11.3).

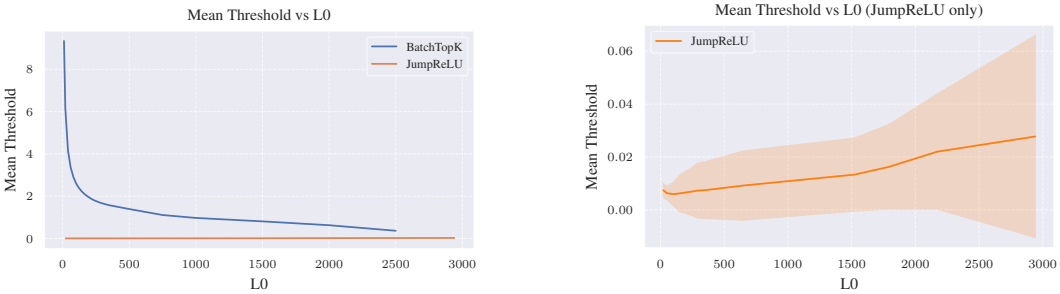

Figure 17: Threshold vs L0 for JumpReLU and BatchTopK SAEs. Shaded area in plots corresponds to 1 stdev. Interestingly, JumpReLU threshold is much lower than the BatchTopK threshold, and actually increases as L0 increases. We plot just JumpReLU on its own (right) since it is otherwise difficult to see these trends, as the threshold is so much smaller than BatchTopK.

A.11.3 Can L0 be both too low and too high simultaneously?

In Figure 15 (right), we plot decoder histogram projection plots for BatchTopK SAEs on Gemma-2-2b layer 12 with L0 10, 200, 750, and 2000. As we expected from Figure 18, when L0 is very low (10) or very high (2000), we see a wide gaussian around 0, indicating that decoder latents are mixing correlated features together. At L0=200, we see a much more narrow distribution around 0, as we expect when near the correct L0. However, at L0=750, we see an interesting phenomenon, where there is an even narrower distribution than at L0=200, but also a large hump starting at projection above 10 (more visible in the log plot).

We suspect this indicates at L0=750, some latents become more monosemantic while other latents mix underlying features becoming less monosemantic. This likely means that the L0 is too high for some latents while simultaneously being too low for other latents. There is no reason why every latent has the same optimal L0 threshold, so there is likely a range of L0s where some latents are firing more than they ideally should while other latents are firing less than they ideally should. We

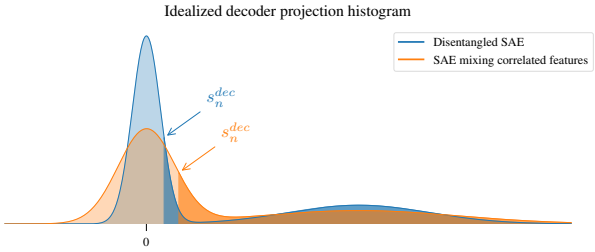

Figure 18: Idealized histogram of decoder projections on input activations demonstrating the intuition behind our n^{th} decoder projection metric, s_n^{dec}. For an arbitrary input, most latents should be non-active and thus have low projection. When SAE latents are monosemantic, we expect non-active latents to have a near-zero projection on arbitrary input activations. However, if SAE latents mix positive and negative components of many underlying features, then those latents will have larger projections on arbitrary inputs that contains those features. By picking an N less than $h/2$, a smaller s_n^{dec} means latents have smaller projection on arbitrary inputs and thus are more monosemantic.

also suspect this is part of why JumpReLU SAEs seem to perform much better at high L0, since JumpReLU SAEs can adjust firing threshold per-latent while BatchTopK SAEs cannot.

A.11.4 Extended Nth decoder projection plots

In this section we document n^{th} decoder projection plots for multiple values of N for each sweep of L0 we performed. We show Llama-3.2-1b layer 7 plots in Figure 21, Gemma-2-2b layer 5 in Figure 19, and Gemma-2-2b layer 12 in Figure 20. We note that in all cases, low L0 behavior is similar: no matter the value of N, s_n^{dec} increases dramatically at low L0. However, the high L0 behavior is less consistent. We always see a similar "elbow" in the plots at roughly the same place regardless of N, but sometimes this elbow corresponds to a clear global minimum, and sometimes the high L0 behavior is very shallow. We find that using a N near $h/2$ (16k in our cases) seems to give the best results.

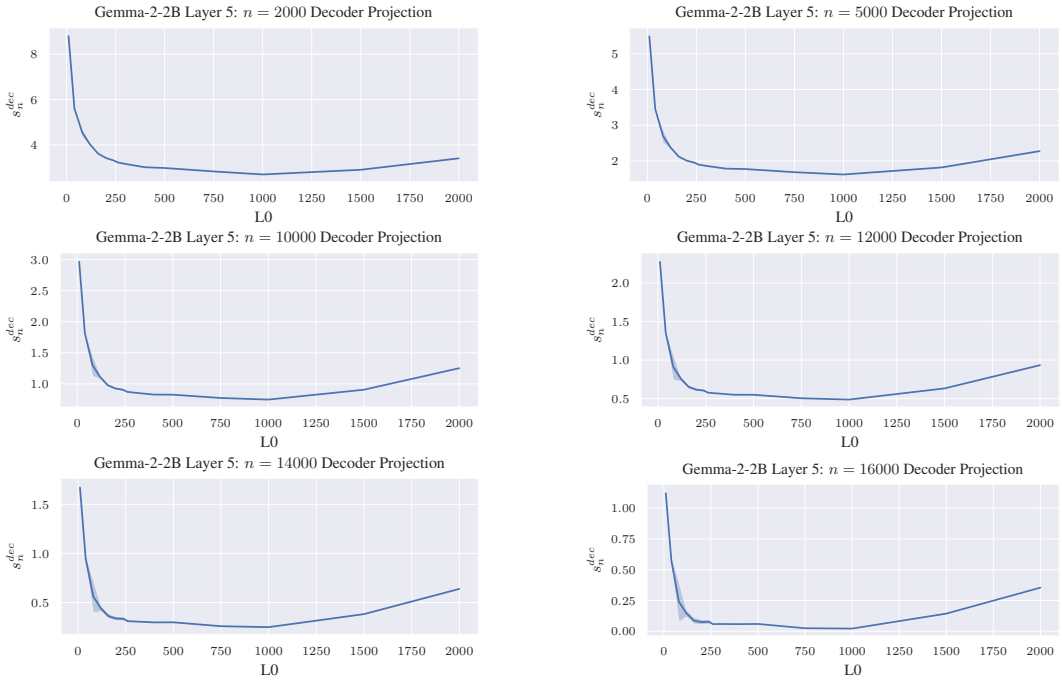

Figure 19: Extended Nth decoder projection plots. Gemma-2-2b, layer 5, 32k latents. These plots never have a clear global minimum at the "elbow" point, but the "elbow" is always at the same point regardless of choice of N.

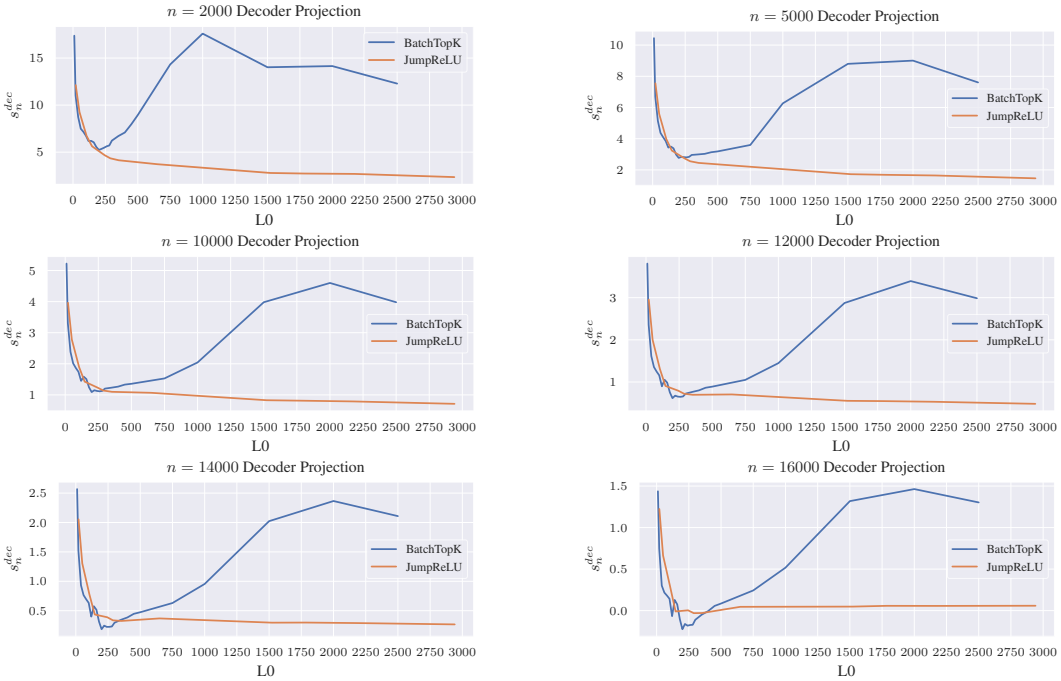

Figure 20: Extended Nth decoder projection plots. Gemma-2-2b, layer 12, 32k latents for both JumpReLU and BatchTopK. For BatchTopK, regardless of the choice of N, all plots are minimized around the same L0 range, 200-250. For JumpReLU, there is a clear "elbow" at roughly the same L0, but this elbow is only a clear minimum at N=16k.

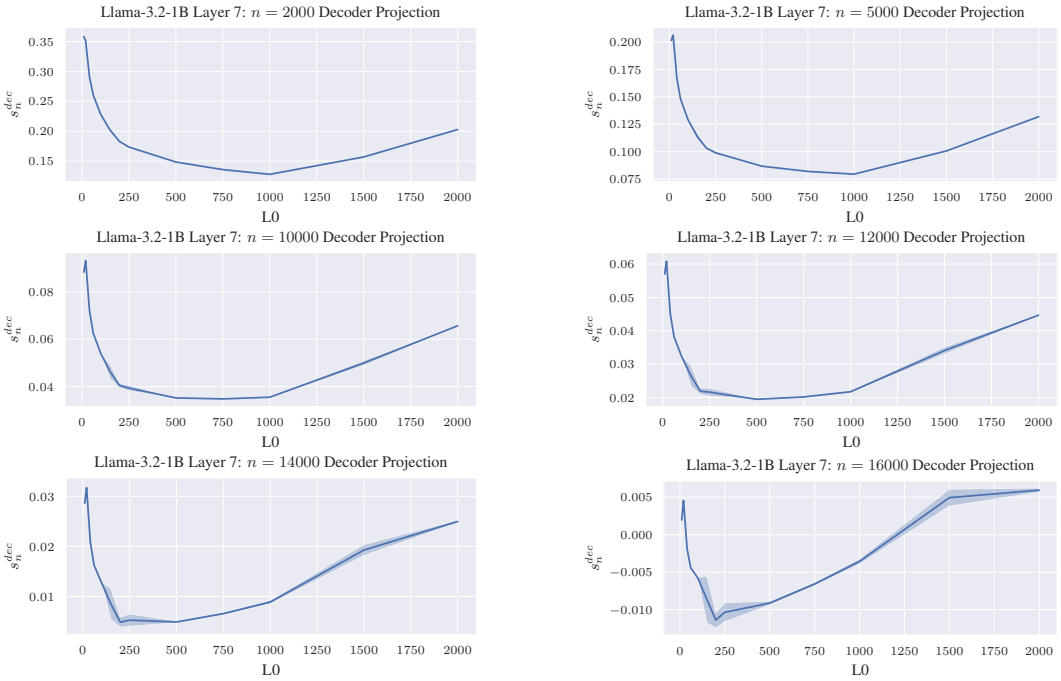

Figure 21: Extended Nth decoder projection plots. Llama-3.2-1b, layer 7, 32k latents. The plots begin to have a sharp minimum around N=14k, but the "elbow" of the plots before the decoder projection increases at low L0 is always around the same location.