

Evaluation of Sparse Autoencoder-based Refusal Features in LLMs: Dataset-dependence study

Master Thesis Proposal

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1 Problem Statement

A key challenge in safely deploying large language models (LLMs) lies in ensuring that they consistently refuse to respond to unsafe prompts while still engaging constructively with safe ones [2]. Refusal in this context describes the model's ability to recognise and reject inputs that could lead to harmful, unethical, or otherwise inappropriate outputs, ensuring alignment with safety and ethical standards.

Although fine-tuning (FT) on curated datasets has been the predominant solution for achieving refusal behavior in large language models, it often struggles to generalize beyond its training distribution, when exposed to adversarial or multi-turn prompts. Without explicit adversarial training, FT is prone to overfitting, resulting in brittle performance under adversarial conditions and complex multi-turn interactions [27, 30]. Even with adversarial training, models still exhibit notable limitations in maintaining robustness and generalization. Further, achieving reliable refusal behavior often requires reinforcement learning from human feedback (RLHF) to better align models with human preferences and mitigate issues such as hallucination or misalignment [7].

To address these limitations and foster understanding of the workings of these models, recent research has begun exploring methods that intervene on the model's activations at inference time - referred to as feature steering - rather than relying solely on weight updates through fine-tuning [19, 10, 9, 21, 15, 29, 31].

An emerging method for feature steering leverages sparse autoencoders (SAEs) [21, 2] trained on a model's activations (please also refer to Figure 2b and Figure 1). SAEs aim to

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discover a more interpretable, disentangled representation of the neural computations underlying a model’s behaviour. In the context of SAEs, interpretability implies that individual latent dimensions correspond to distinct features, such as refusal tendencies, and can be understood and controlled explicitly. Central to this effort is the superposition hypothesis [11]: large neural networks often pack a vast number of distinct features into a limited set of neurons by representing them as overlapping vectors in a high-dimensional space. This compression, known as polysemanticity, can cause a single neuron or dimension to encode multiple, conceptually unrelated features [11, 6]. While polysemantic encoding efficiently utilizes available resources, it hinders mechanistic interpretability - making it challenging to isolate the features that mediate specific behaviours, such as refusals.

SAEs provide a potential solution by learning a sparse, over-complete basis for the model’s hidden representations. In doing so, they strive to “decompress” this polysemantic tangle into more monosemantic features - i.e., more directly interpretable latent dimensions that correspond to distinct, coherent concepts or behaviours ([6, 11, 2], also refer to [20, 10, 25]).

By training an SAE on the model’s activations, we can identify latent features that strongly correlate with refusal behaviour. Once identified, these features can either be manipulated at inference time by “steering” them - clamping or shifting their activation values - to encourage or discourage certain responses without retraining the model [21, 1]. Although SAEs are technically trained on a model’s activations rather than the dataset itself, it is common to say that an SAE was trained on a dataset, as the activations originate from a model trained on that dataset [10].

This approach complements existing safety methods, offering the potential to improve generalisation and adapt while leaving the model’s underlying parameters untouched.

2 Goals and Expected Outcome

This research aims to evaluate the effectiveness of SAEs for improving refusal behaviour in LLMs. By examining the dependency of SAE performance on dataset characteristics, this work seeks to identify key properties such as distributional diversity and the prevalence of refusals that contribute to robust and interpretable feature disentanglement.

3 Goals and Expected Outcomes

This research aims to advance the understanding of SAEs in disentangling refusal-related features in LLMs by addressing dataset dependencies and their implications. The key outcomes of this work are:

1. **Identification of Dataset Characteristics for Robust SAE Features:** Establish the properties of datasets, such as topical diversity and prevalence of refusal instances, that contribute to robust, interpretable, and effective SAE-extracted features for refusal behaviour.
2. **Evaluation of SAE-based Refusal Features:** Quantify the robustness, interpretability, and generalisability of SAE-extracted refusal features across diverse datasets and

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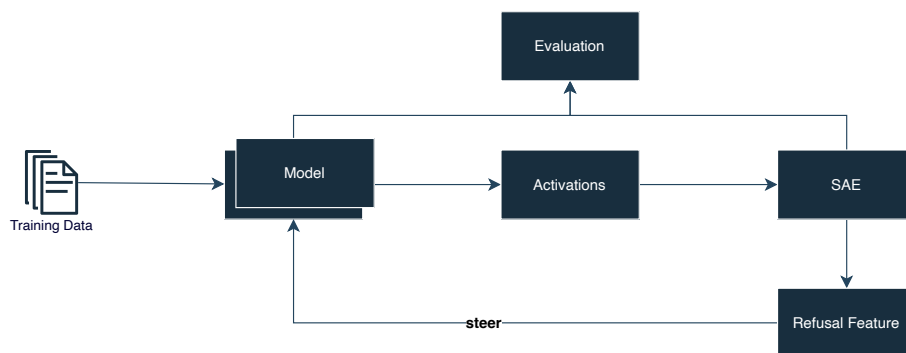


Figure 1: Training and Evaluation flow of models, SAEs and extracted refusal features.

adversarial conditions, providing evidence for their practical viability in enhancing model safety.

3. **Impact Assessment of SAE Features on Model Behaviour:** Assess how SAE-informed refusal features affect downstream performance, safety alignment, and adversarial robustness in language models, establishing their utility without degrading unrelated capabilities.
4. **Contribution to Open and Reproducible Research:** Deliver open-source resources, including datasets, metrics, and evaluation frameworks, to support transparency and reproducibility in mechanistic interpretability research.

4 Research Questions

The following section presents our research questions and explains them.

RQ 1: How does the choice of training dataset affect the sparse autoencoder’s ability to isolate and represent refusal features within a language model’s latent activations?

The focus is on comparing the impact of the original pre-training data against alternative datasets (e.g., chat-refinement data) in shaping the SAE’s capacity to identify refusal-related features from model activations. To properly conduct this evaluation we rely on fully open-source models.

RQ 2: Which characteristics of the underlying training data are most predictive of the strength and clarity of SAE-extracted refusal features?

The training data indirectly shapes the model’s latent activations, which are the basis for SAE-extracted refusal features. Understanding which dataset characteristics—such as distributional properties, topical diversity, or the frequency of refusals—most strongly influence these activations can help identify the conditions under which refusal-related features emerge most clearly and robustly.

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RQ 3: How do extracted refusal features of sparse autoencoders trained on activations gathered from a model exposed to refined-datasets compare to those trained on acti-

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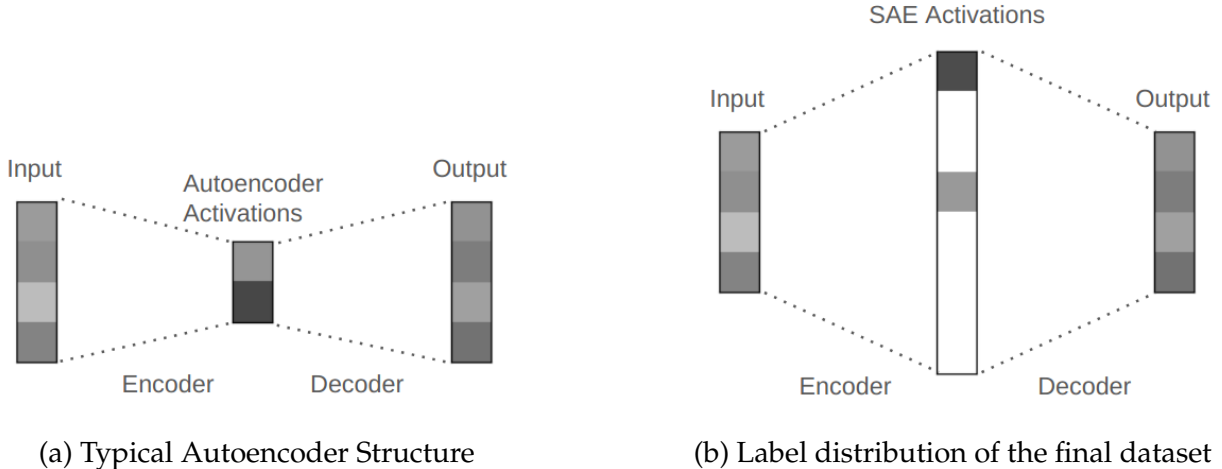


Figure 2: Comparative visualisation of Autoencoders (a) to Sparse Autoencoders (b), taken from Karvonen [20].

variations gathered from a model exposed to the original pre-training corpus, in terms of robustness, interpretability, downstream performance and controllability of refusal-related features?

The activations gathered from a model reflect its internal representations, which are influenced by the datasets it was exposed to during training. By comparing SAEs trained on activations from models conditioned on refined datasets versus the original pre-training corpus, we can evaluate how the choice of data impacts the robustness, interpretability, and downstream controllability of refusal-related features.

5 Methods

Following, we detail our methodological approach. Please also refer to Figure 1 for an overview of the connection and flow of the different components. As evaluation is a crucial part in this research please also refer to section 6 for further details.

5.1 Models and Configurations

At the core of our experiences are the Pythia model family [5] which was specifically designed to be analysed and has its entire code [5, 4, 13] and data [3] open source. Here we look at the different sizes (from 410m - to 2.8b). Firstly, we need to extract which model is the first one to exhibit a refusal behaviour that can properly be evaluated. E.g. pythia 70m often just repeats the prompt or produces gibberish. Further models we might analyse is the e.g. OLMo model [14] which is also a fully open model.

5.2 Training SAEs

SAEs reconstruct neural network activations into a sparse, overcomplete basis, isolating *disentangled features* that address the challenge of polysemantic neurons [11, 20, 22, 2, 19].

SAEs consist of an encoder and decoder, where the encoder maps input activations $x \in \mathbb{R}^d$ to a sparse higher-dimensional representation $h \in \mathbb{R}^n$ (with $n > d$), and the decoder

reconstructs x from h . Formally,

$$h = \sigma(W_{\text{enc}}x + b_{\text{enc}}), \quad x' = W_{\text{dec}}h,$$

where W_{enc} , W_{dec} , and b_{enc} are learned parameters. σ denotes the activation function, ReLU is a common choice. The training objective minimizes the reconstruction loss while enforcing sparsity via an ℓ_1 -norm penalty:

$$L(x) = \|x - x'\|^2 + \alpha \|h\|_1,$$

where α controls the trade-off between accuracy and sparsity. The resulting sparse features, corresponding to specific linear directions in activation space, disentangle overlapping representations and enable interpretable analysis. These features can be *steered* (amplified or suppressed, for more details refer to subsection 7.2 to analyse and manipulate behaviours (e.g., refusal tendencies in language models). SAEs thus provide an effective tool for isolating monosemantic features and advancing mechanistic interpretability.

Please also refer to Figure 2a and Figure 2b for a comparative visualisation of autoencoders versus sparse-AEs.

5.2.1 Pre-Training SAE

Train SAEs on activations from the base - model (pre-training) dataset.

5.2.2 Post-Training SAE

Train SAEs on activations derived from a post-training dataset.

5.3 Refusal Feature Extraction

Following [1], [21], and [10] we extract the refusal features by XXXXXXXX.

6 Evaluation

We assess the performance of the gathered models, SAEs trained on the models activations and models steered by refusal features extracted from the SAEs along the following dimensions. Phase 1 however only applies to the SAEs itself.

The evaluation is structured into three distinct phases, following well-established and proven methodologies and metrics (see [9] for reference).

6.1 Phase 1: SAE Quality Metrics

This phase focuses on evaluating the SAEs independently to verify their effectiveness in reconstructing and sparsely encoding model activations.

6.1.1 Reconstruction Error

We measure how accurately each SAE reconstructs the original activation patterns of the language models. Reconstruction quality will be quantified by minimizing the loss between input activations and their SAE-generated reconstructions.

6.1.2 Sparsity

To ensure and evaluate how much the extracted features remain interpretable and disentangled, we calculate the fraction of non-zero activations in the sparse vector representation produced by the SAEs. Sparsity metrics will follow prior work, as described by Arditi et al. [1].

6.2 Phase 2: Refusal

This phase investigates how refusal-related features, extracted via SAEs, influence the models’ refusal behavior across safe and unsafe instructions. By enabling or disabling SAE-informed refusal features, we can measure their direct impact on refusal and over-refusal rates, isolating the effect of these features on model behavior. We closely follow the methodology of Kissane et al. [9] and Arditi et al. [1].

6.2.1 Refusal Rate

We evaluate the models’ ability to refuse unsafe prompts, measuring refusal frequency using benchmarks like Wild Guard [16] and JailbreakBench [8]. Refusal will be detected by identifying common refusal phrases in model completions.

6.2.2 Over-refusal Rate

To ensure the refusal features do not inadvertently reduce the models’ compliance with benign prompts, we measure the over-refusal rate for safe instructions. This evaluation compares model outputs for paired safe and unsafe instructions.

6.3 Phase 3: Robustness and Downstream Performance

In this phase, we assess the broader impact of SAE-informed refusal features on model robustness, reasoning, and general performance across tasks. Comparisons will be conducted across four configurations: the base model, the chat-tuned model, and their respective SAE-enhanced counterparts. We explicitly disable identified refusal features or use neutral feature clamping (e.g., setting activations to zero or a baseline value) to quantify their specific contributions to task performance and refusal robustness. These ablations help evaluate whether refusal features interfere with unrelated capabilities or improve safety alignment.

6.3.1 Massive Multitask Language Understanding (MMLU)

We employ the MMLU benchmark [17] to evaluate the models’ overall reasoning and performance across diverse tasks. This analysis focuses on determining how the integration of refusal features impacts capabilities unrelated to refusals.

6.3.2 Jailbreak Robustness

We test model robustness against adversarial prompts designed to bypass refusal mechanisms using benchmarks like JailbreakBench [8]. Multi-turn evaluation setups, similar to those in [9], will be used to analyze the models’ resilience to jailbreak attempts and the effectiveness of SAE-informed refusal features.

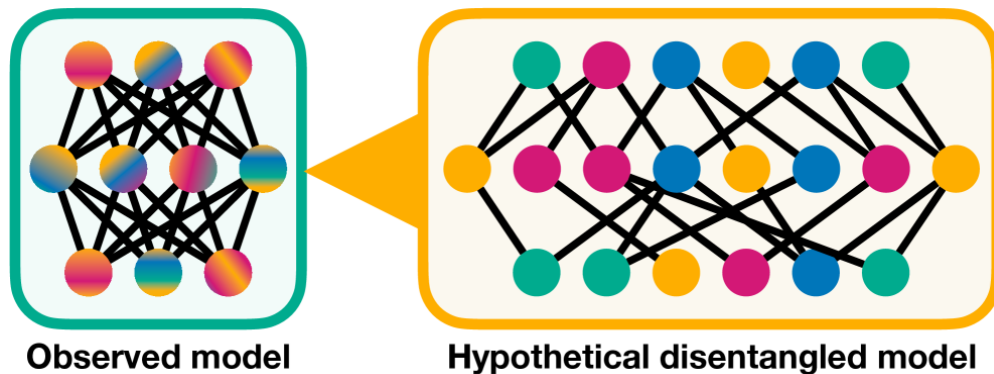


Figure 3: Visual representation of superposition and disentanglement in neural networks, taken from Bereska et al. [2].

6.3.3 Baseline Comparisons

To establish a clear understanding of the effects introduced by the SAEs, we conduct baseline comparisons with standard models (base and chat-tuned) that do not include SAE-informed modifications. This includes ablation studies to isolate and evaluate the specific contributions of the refusal features:

7 State of the Art

This section covers current approaches in the field of mechanistic interpretability related to our research. While not recent, we would like to mention the foundational work of Elhage et al. [12], and Nanda (i.a. [25, 26, 24, 23]). Further, we would explicitly like to mention the recent study from Bereska et al. [2] that reviews the current state and established concepts and frameworks in the field.

7.1 Sparse Autoencoders and Superposition

The concept of sparse autoencoders (SAEs) was introduced by Makhzani et al. in 2013 [22] but their application gained renewed interest following Elhage et al.’s 2022 superposition hypothesis [11] and following work [28, 6].

Theoretical analyses using toy models [11] validate the occurrence of superposition under conditions of feature sparsity and limited neurons, with SAEs successfully recovering disentangled representations in these scenarios. Also scaling this approach to more complex, state-of-the-art models has proven effective, with recent work demonstrating that SAEs can extract interpretable and monosemantic features even in large-scale systems [28].

For a visual representation, please refer to Figure 3. The observed model (left) demonstrates polysemanticity, where individual neurons encode multiple features, leading to overlapping and entangled representations. In contrast, the hypothetical disentangled model (right) illustrates monosemanticity, where each neuron clearly encodes a single, distinct feature.

Features SAEs

7.2 Steering Large Language Models

Steering generally refers to manipulating the output of LLMs by employing XXXXXX [2]. Various ways to address this have been proposed, and developed [18, 31, 29, 15]. Use cases for steering are manifold - jailbraiking, performance improvement, alignment and safety.

7.3 Refusal of Harmful Content

As already mentioned in section 1, current approaches mostly use some form of adversarial prompt tuning [27, 30] and or in combination with RLHF [7]. Other current research shows xxxx // see [1] and [2] for inputs.

SAE- refusal related are mainly: [9, 10, 21].

8 Relevance to the Curriculum

This work tries to explore and uncover the workings of generative decoder transformer models working with natural language. Thus, bringing together various aspects from different courses and core elements of the Data Science and Informatics curriculum. Courses such as Machine Learning (188.702), NLP and Information Extraction (194.093), and Applied Deep Learning (194.077) have provided a strong foundation in machine learning techniques, including deep learning architectures central to transformer models. Additionally, Advanced Information Retrieval (188.980), which explores state-of-the-art retrieval techniques like BERT-based models, directly supports this research's focus on identifying and refining task-specific circuits within language models.

The course Research Topics in Natural Language Processing (194.135) has introduced advanced methodologies specific to NLP, equipping me with essential research skills in e.g. examining model interpretability and ethical behaviour in language models.

Additional expertise in handling complex data systems, as developed and studied in Advanced Database Systems (184.780) and Data-intensive Computing (194.048), is critical for the large-scale model processing and analysis involved in this work. Furthermore, courses like Information Visualisation (186.143) and Visual Data Science (186.868) provide a solid foundation in visualising complex data, which will be crucial in effectively communicating the results of model circuit analysis and interventions.

9 Overall Review

The conducted literature research establishes a solid foundation for this work by demonstrating the potential of SAEs to disentangle and analyse latent features, particularly for safety-critical behavior such as refusals. Existing studies have highlighted the importance of dataset composition [10] in shaping learned behavior, but the interplay between training data characteristics and SAE performance remains under explored. This proposal will extend these findings by systematically addressing the outlined research questions, examining how dataset choices and properties influence the extraction, robustness, and controllability of refusal features, ensuring a comprehensive understanding and progression of this research area.

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