Master's Thesis Proposal

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

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Refusal

Model's ability to **identify and reject** inputs that could lead to **harmful, unethical**, or otherwise **inappropriate outputs**

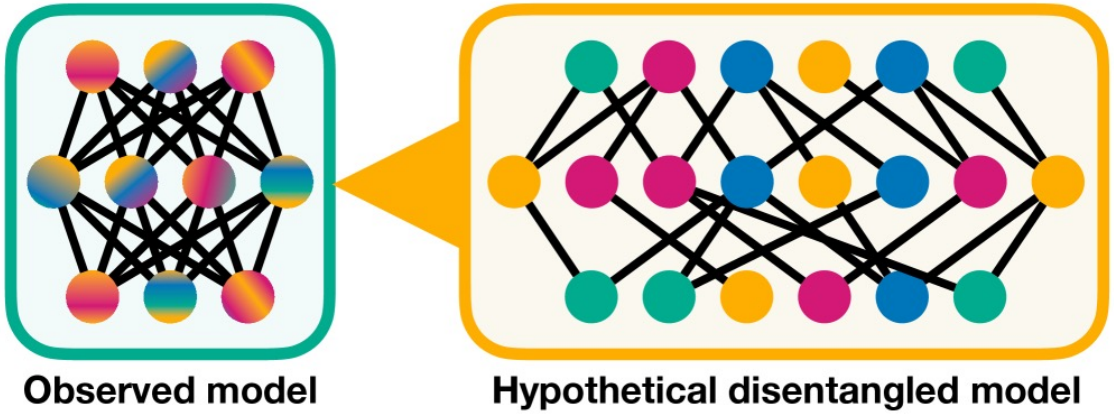
SOTA Refusal

- Base Models Refuse Too
- Fine-tuning
- Reinforcement-learning with HF
- Adversarial Training

[4] [10] [14] [28] [36] [39] [42]

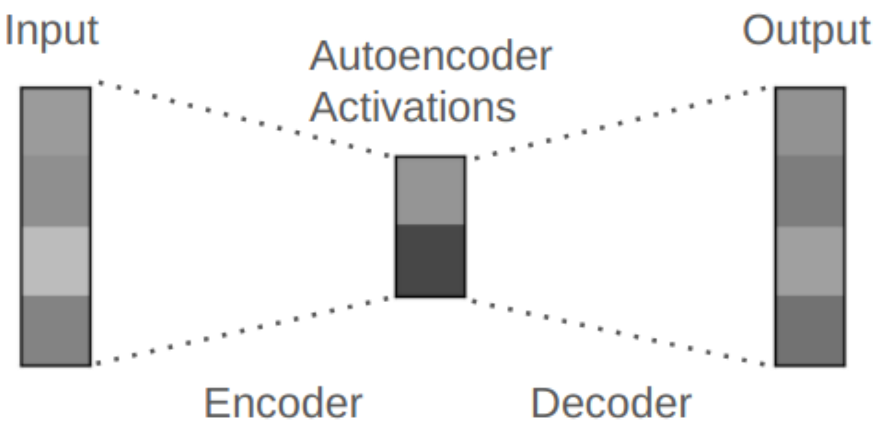
Mechanistic Interpretability

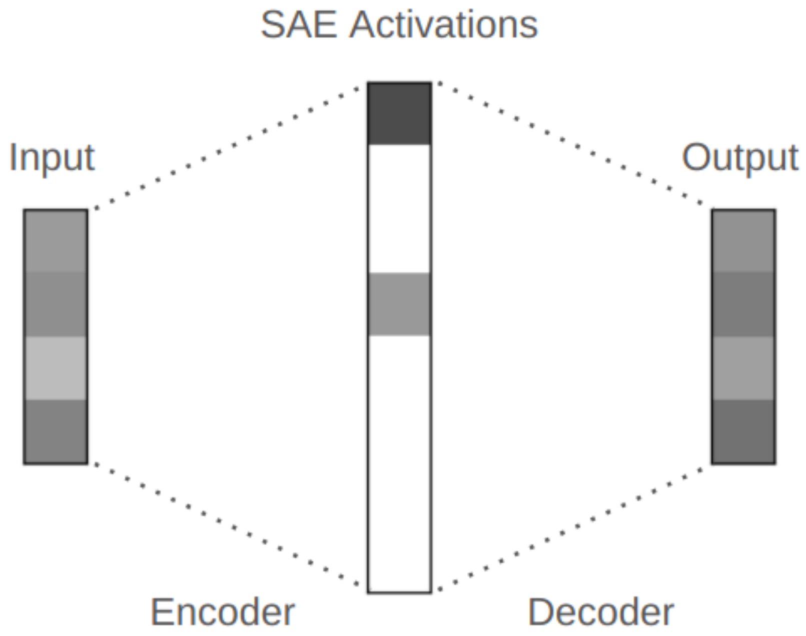
- Reverse Engineering
- E.g. “Understanding” what parts of the model are responsible for what
- Polysemanticity and Superposition
  → *individual neurons or attention heads encode multiple distinct concepts*



BERESKA, L., AND GAVVES, E. Mechanistic interpretability for ai safety – a review, 2024.

Towards Monosemanticity: Sparse Autoencoders (SAEs)

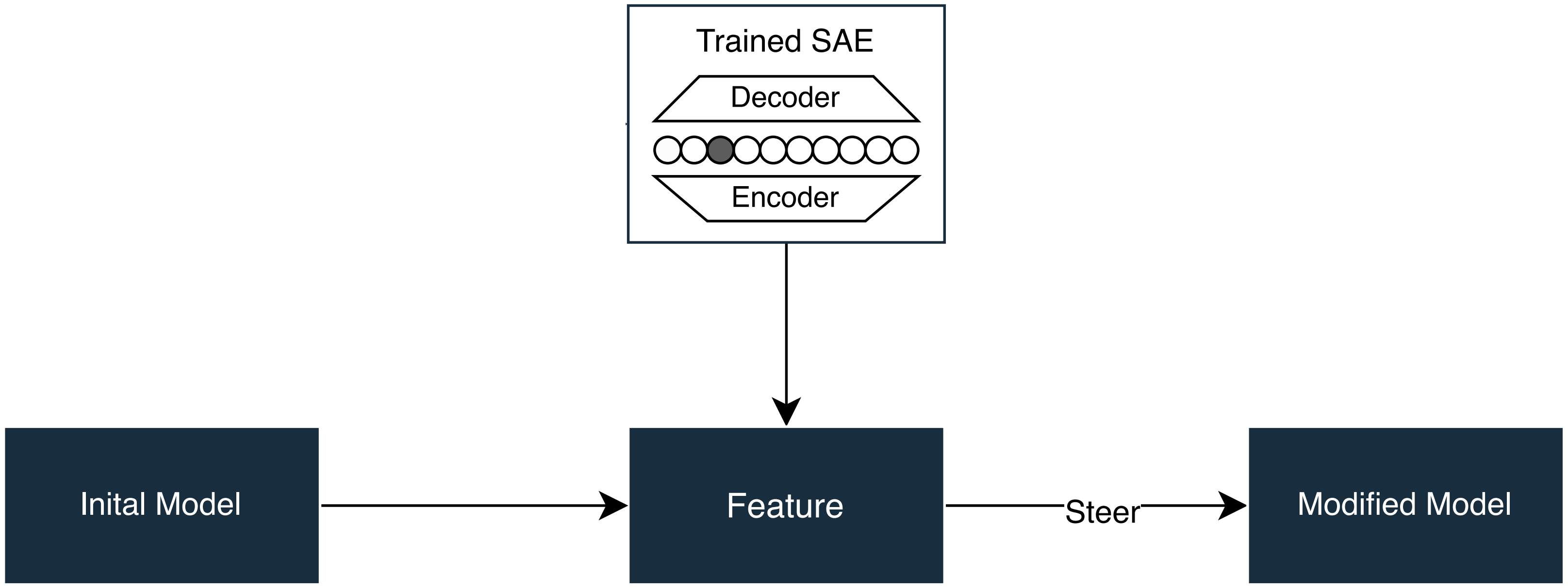




→ learning a sparse, overcomplete basis (input dim. < output dim.)
→ each latent feature corresponds to a distinct, disentangled concept

KARVONEN, A. An intuitive explanation of sparse autoencoders for llm interpretability, Jun 2024. Accessed: 18.12.2024.

Steering with SAEs



→ Extracted features can be altered and used to modify model outputs

Research Questions

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?
2. Which characteristics of the underlying training data are most predictive of the strength and clarity of SAE-extracted refusal features?
3. How do extracted refusal features of sparse autoencoders trained instruction-datasets compare to those trained on the original pre-training corpus, in terms of robustness, interpretability, downstream performance and controllability of refusal-related features?

RQ 1. SAE’s ability to isolate refusal

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., instruction 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.

Metric: Sparsity

RQ 2. Clarity and Strenght of Refusal

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.

Metric: Refusal Score

RQ 3. Comparison Base vs. Instruct Models

How do extracted refusal features of sparse autoencoders trained on instruction-datasets compare to those trained on the original pre-training corpus, in terms of robustness, interpretability, downstream performance and controllability of refusal-related features?

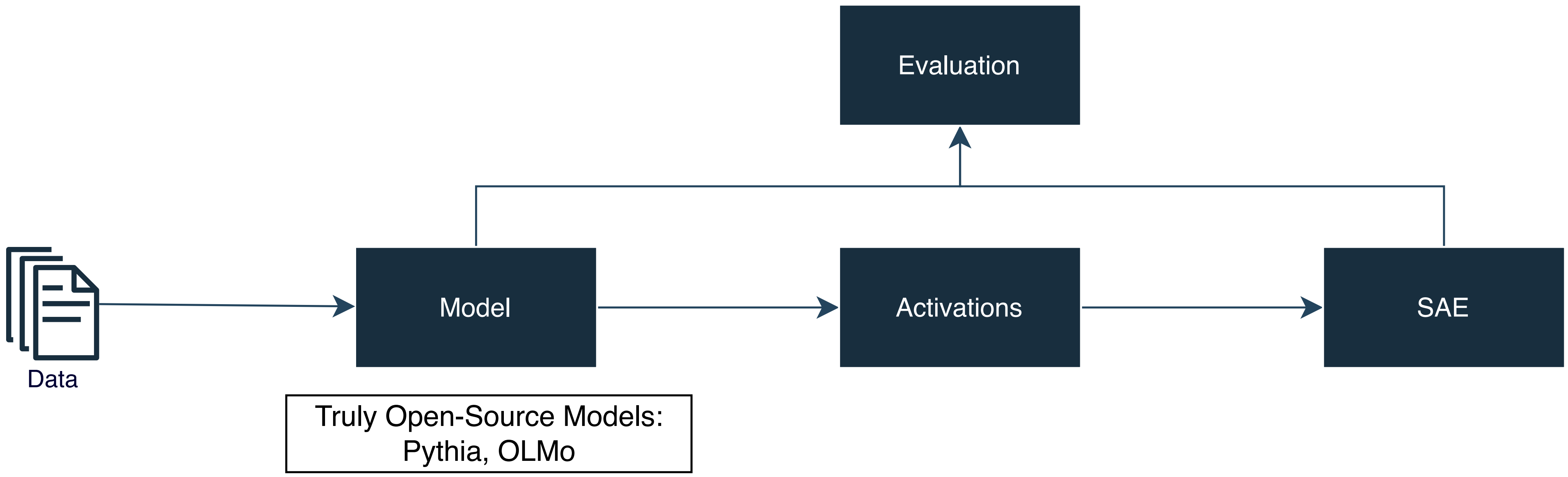
The activations gathered from a model reflect its internal representations, which are influenced by the datasets it was exposed to during training. By comparing SAEs trained on activations from models conditioned on instruction datasets versus the original pre-training corpus, we can evaluate how the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

Metric: Benchmarks (MMLU, ..)

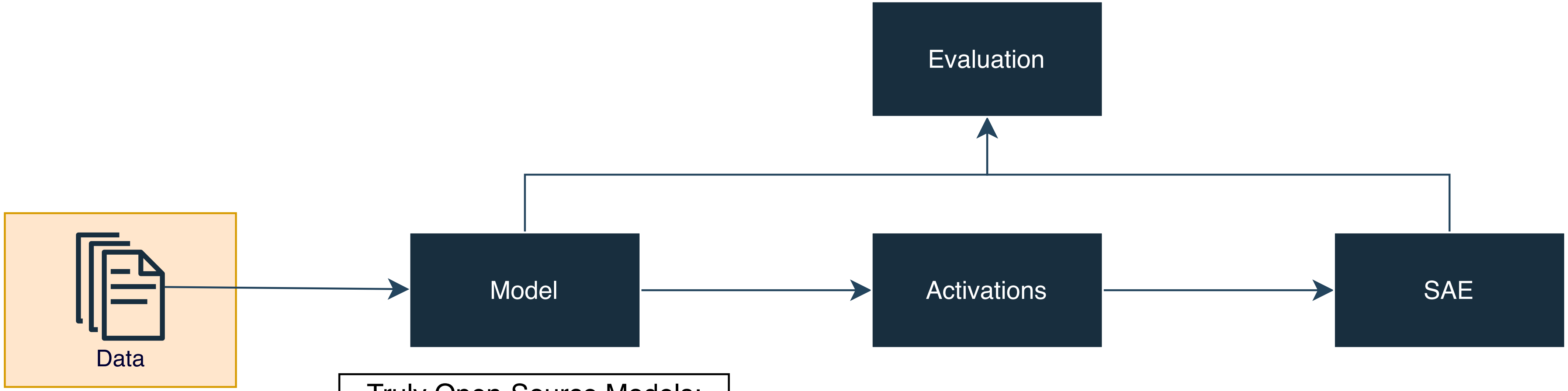
Definitions

- **Robustness:** Maintaining Effectives across varying conditions, including unseen datasets, adversarial inputs, and noisy prompts
- **Interpretability:** Individual latent dimensions correspond to distinct features, such as refusal tendencies that can be understood and controlled explicitly
- **Controllability:** Altering extracted and identified features/dimensions influences the output of a model
- **Clarity:** This dimensions alters / represents the desired concept

Methodology: SAE Collection



Methodology: Dataset characterisation



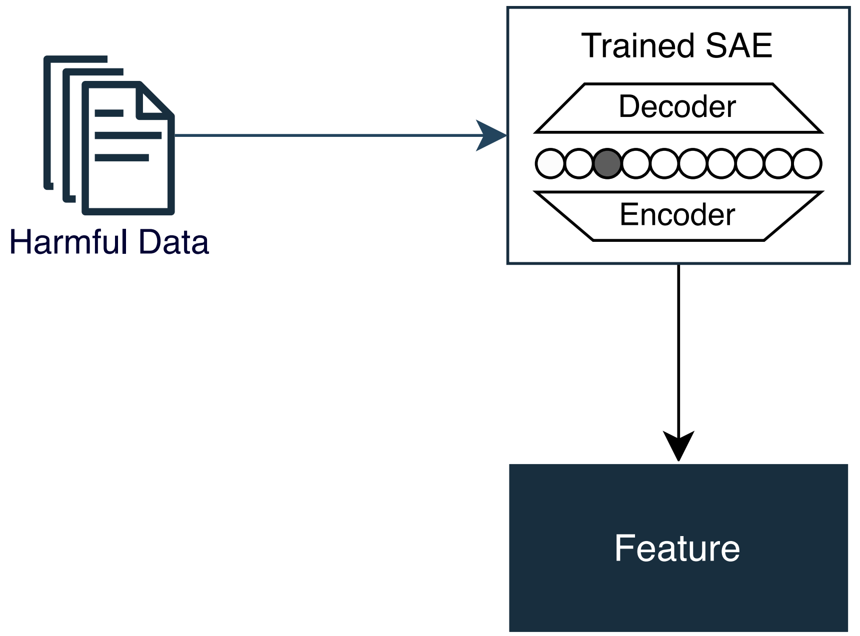
Calculate characteristics: e.g. vocabulary size, n-gram diversity, …

Truly Open-Source Models: Pythia, OLMo

[5] [12]

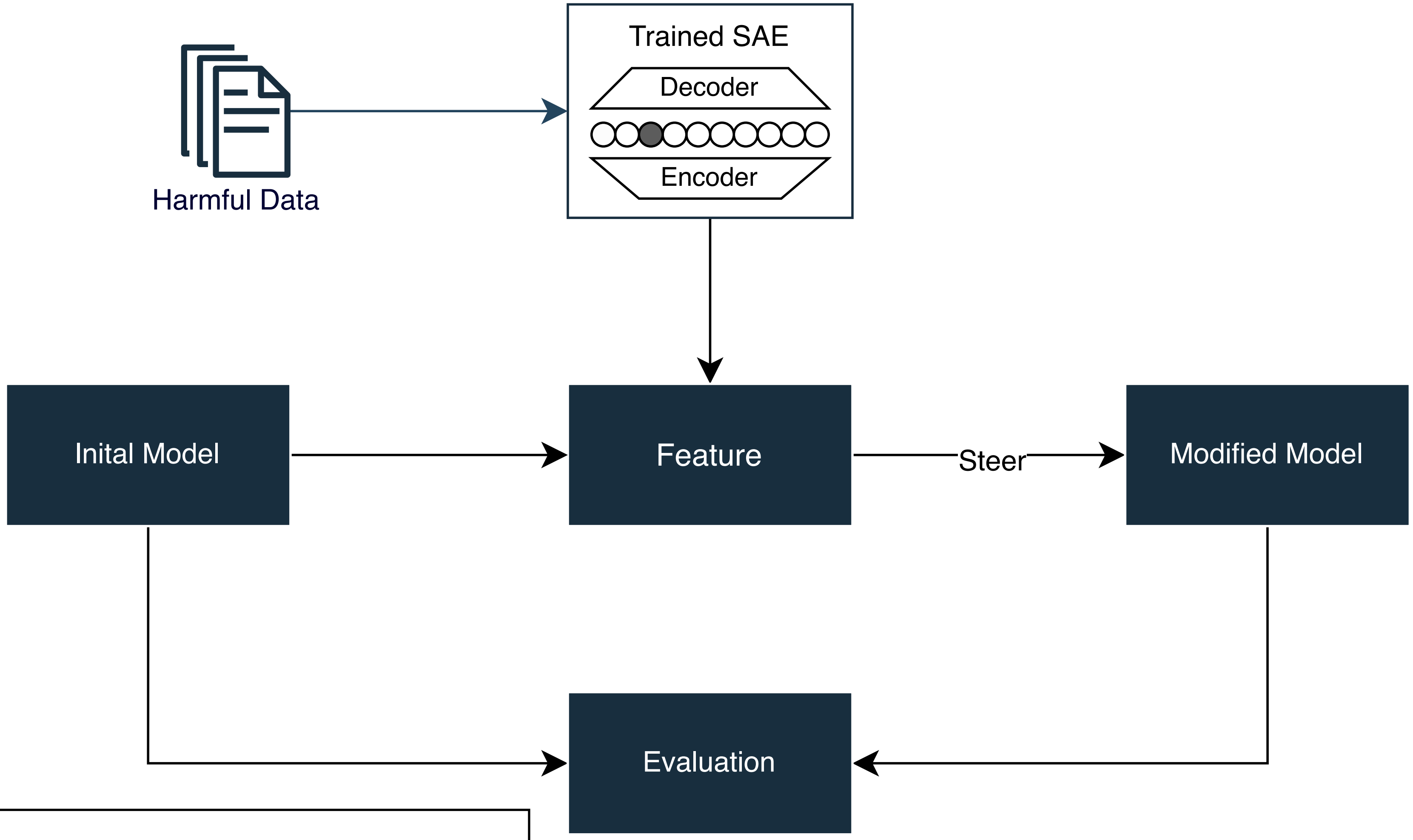
Methodology: Feature extraction with SAEs

Using targeted data to identify respective featues (dimensions)



[5] [13] [34]

Methodology: Steering and Evaluation



[5] [13] [34]

Evaluation

SAE

- Reconstruction Error
- Sparsity

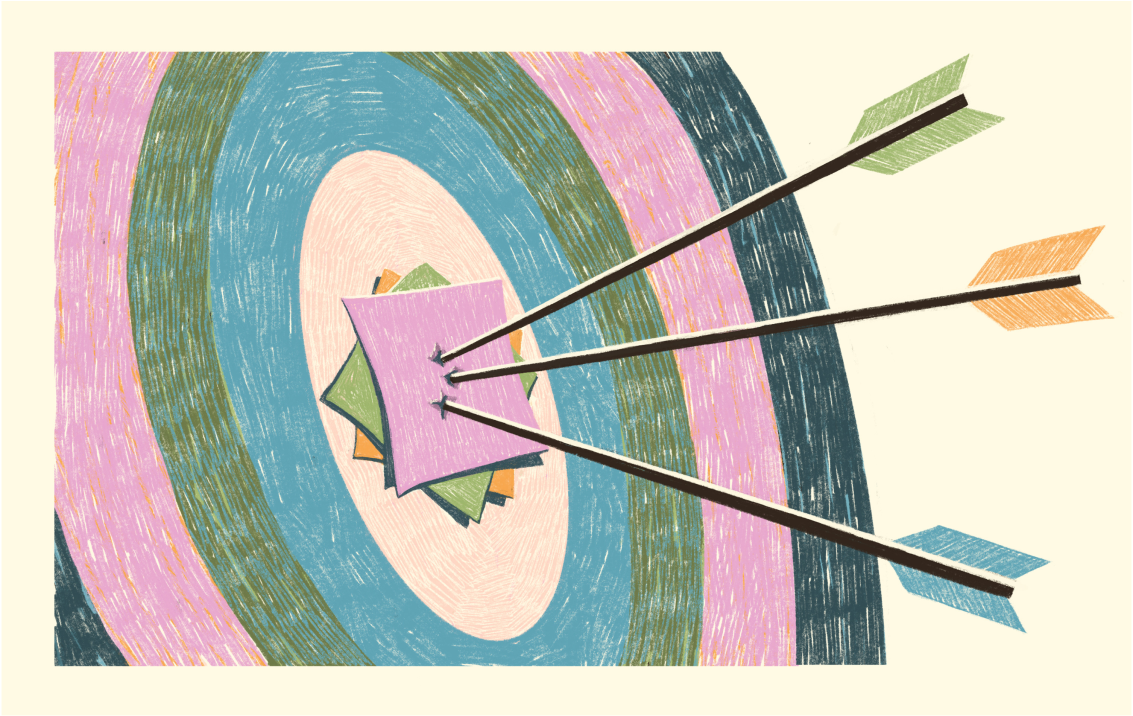
Refusal

- Refusal Rate
- Over-refusal Rate

Performance

- MMLU
- Jailbreak Robustness Benchmark

Expected Outcome



- Identification of Dataset Characteristics for Robust SAE Features
- Identification of Limitations of SAEs and SAE steering
- Comprehensive Impact Assessment of SAE Features on Model Behaviour

Thank You

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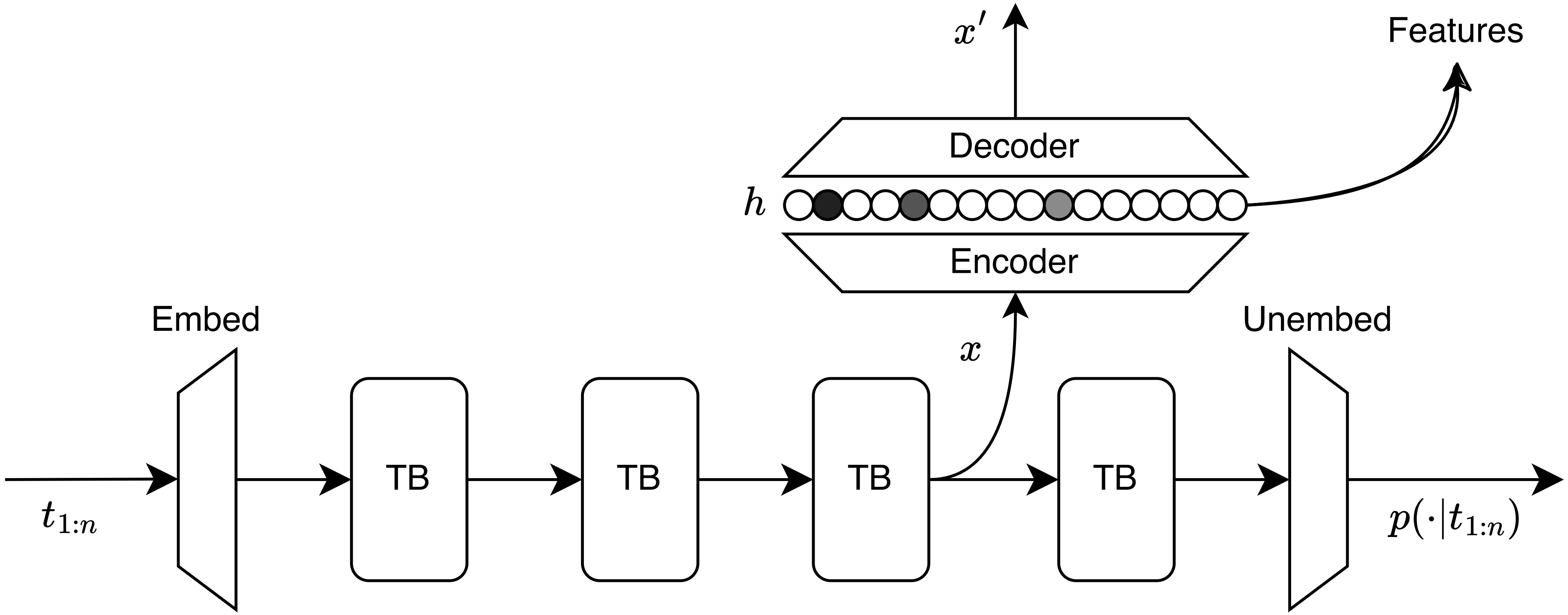
Backup in case of questions

Feature Identification with SAEs



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