Feature-Level Insights into Artificial Text Detection with Sparse Autoencoders

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Abstract

Artificial Text Detection (ATD) is becoming increasingly important with the rise of advanced Large Language Models (LLMs). Despite numerous efforts, no single algorithm performs consistently well across different types of unseen text or guarantees effective generalization to new LLMs. Interpretability plays a crucial role in achieving this goal. In this study, we enhance ATD interpretability by using Sparse Autoencoders (SAE) to extract features from Gemma-2-2B's residual stream. We identify both interpretable and efficient features, analyzing their semantics and relevance through domain- and model-specific statistics, a steering approach, and manual or LLM-based interpretation of obtained features. Our methods offer valuable insights into how texts from various models differ from human-written content. We show that modern LLMs have a distinct writing style, especially in information-dense domains, even though they can produce human-like outputs with personalized prompts. The code for this paper is available at https://github.com/pyashy/SAE_ATD.

1 Introduction

The active development of large language models (LLMs) has led to the increasing presence of AI-generated text in various domains, including news, education, and scientific literature. Although these models have demonstrated impressive fluency and coherence, concerns about misinformation, plagiarism, and AI-generated disinformation have required the development of reliable artificial text detection (ATD) systems (Abdali et al., 2024). Existing ATD frameworks primarily rely on statistical measures, linguistic heuristics, and deep learning classifiers, yet these methods often lack interpretability, limiting their reliability in high-stakes applications (Yang et al., 2024).

A promising approach to enhancing interpretability in ATD is the use of Sparse Autoencoders (SAEs), which learn structured representations of textual data by enforcing sparsity constraints (Huben et al., 2023; Makelov et al., 2024). We can extract human-interpretable features that capture the underlying structure of text.

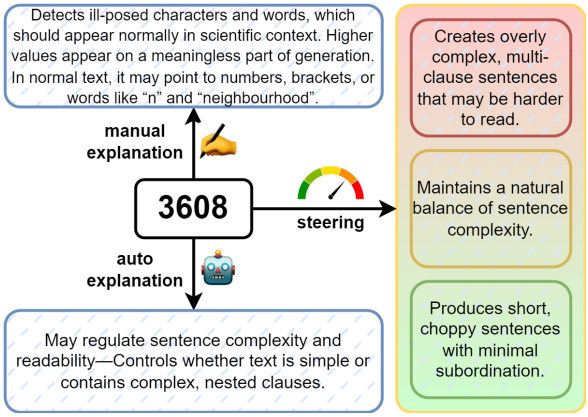

Figure 1: Interpretations of one of the most "universal" SAE features that are useful for ATD task.

In this study, we extend this line of research by applying SAEs from the Gemma-2-2b model (Team, 2024a) residual streams to analyze features that contribute to artificial text detection. By examining these features, we introduce a categorization of extracted features into discourse features (capturing long-range dependencies), noise features (highlighting unnatural artifacts), and style features (distinguishing stylistic variations). Our contributions are the following:

(i) we demonstrate the efficiency of SAE for the ATD task; (ii) we extract features which alone can effectively detect artificial texts for some domains and generation methods; (iii) interpreting these features, we identify meaningful patterns that contribute to ATD interpretability.

For our main dataset, we utilized a highly comprehensive and up-to-date dataset from GenAI Content Detection Task 1 – a shared task on binary machine-generated text detection, conducted as

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part of the GenAI workshop at COLING 2025 (Wang et al., 2025). Hereafter referred to as the COLING dataset, it contains a diverse range of model generations, from mT5 and OPT to GPT-4o and LLaMA-3. A complete list of models, along with generation examples, is provided in Appendix C.

We also performed additional experiments on the RAID dataset (Dugan et al., 2024), which contains generations from several models with various sampling methods and a wide range of attacks, from paraphrasing to homoglyph-based modifications. We provide the full list of models and attacks, along with examples of generations, in Appendix B.

2 Background

Given a token sequence $(t_1, t_2, ..., t_n)$, an LLM computes hidden representations $\mathbf{x}_i \in \mathbb{R}^d$ at each layer l as $\mathbf{x}_i^{(l)} = g^{(l)}(\mathbf{x}_1^{(l-1)}, \mathbf{x}_2^{(l-1)}, ..., \mathbf{x}_i^{(l-1)})$, where g represents a transformer block, typically including self-attention and feedforward operations. These activations encode meaningful information about text, but understanding models requires breaking them into analyzable features. Individual neurons are limited as features due to polysemanticity (Olah et al., 2020), meaning that models learn more semantic features than there are available dimensions in a layer; this situation is referred to as superposition (Elhage et al., 2022b). To recover these features, a Sparse Autoencoder (SAE) has been proposed to identify a set of directions in activation space such that each activation vector is a sparse linear combination of them (Sharkey et al., 2023).

Given activations $\mathbf{x}$ from a language model, a sparse autoencoder decomposes and reconstructs them using encoder and decoder functions with some activation function σ:

$$f(\mathbf{x}) = \sigma(\mathbf{W}_{\text{enc}}\mathbf{x} + \mathbf{b}_{\text{enc}})$$

$$\hat{x}(f) = \mathbf{W}_{\text{dec}} f(\mathbf{x}) + \mathbf{b}_{\text{dec}}$$

for which $\hat{x}(f(\mathbf{x}))$ should map back to $\mathbf{x}$. Here, the sparse and non-negative feature vector $f(\mathbf{x}) \in \mathbb{R}^M$ (with $M \gg d$) specifies how to combine columns of $\mathbf{W}_{\text{dec}}$ which is learned features, or *latents* in order to reconstruct $\mathbf{x}$.

3 Methods

In this work, we take a step towards improving the interpretability of artificial text detection using SAEs. We employ the Gemma-2-2B model along with pre-trained autoencoders on residual streams from Gemma-Scope (Lieberum et al., 2024).

Classifier models. For each even layer, we utilize an individual SAE $(f^{(l)}, \hat{x}^{(l)})$ to extract learned features from each token. To obtain a feature vector $\mathbf{f}$ representing the entire text for layer l, we sum over all tokens, yielding

$$\mathbf{f} = \sum_{i=1}^{n} f^{(l)}(\mathbf{x}_i^{(l)})$$

We use an XGBoost classifier to evaluate the expressiveness of the full feature sets for each layer and identify the most important features for further analysis[1], while LLM and SAE models remain frozen. The classifiers are trained exclusively on the Train subset of COLING and evaluated on the similar Dev set, as well as on the entirely distinct Devtest and Test subsets.

Additionally, we employ indicator functions of the form $\mathbb{I}[\mathbf{f}_j > \tau]$ as threshold-based classifiers on individual features for a detailed feature analysis. To obtain the optimal classifier $\mathbb{I}_{\tau^*}$, we determine the threshold τ^* using logistic regression on the training data. Furthermore, leveraging the sparsity of the feature vectors, we define classifier $\mathbb{I}_0$ by setting $\tau = 0$. In this setting, we consider feature j to be *activated* in a text if $\mathbf{f}_j > 0$, and *not activated* otherwise.

Manual Interpretation and Feature Steering. For manual interpretation, we analyzed the texts that activate the most expressive features. In layers with strong performance and generalization (layers 8 to 20), we selected the top-20 most significant features identified by XGBoost, as well as all features that achieved the highest detection performance for each domain and model using a threshold classifier. These selected features, their statistical properties, and example texts are publicly available[2].

To examine how learned features affect text generation, we use *feature steering*, which enables targeted modifications by selectively adjusting latent feature activations. For a given feature with index i, associated with a specific text property, we first compute its maximum activation $A_{\max}$ across a reference dataset. During generation, hidden states

[1] We use a pretrained SAE with 16k of features. However, only 1–2% of these features contribute to ATD, based on the top 90% of cumulative gain derived from XGBoost.

[2] https://mgtsaevis.github.io/mgt-sae-visualization/

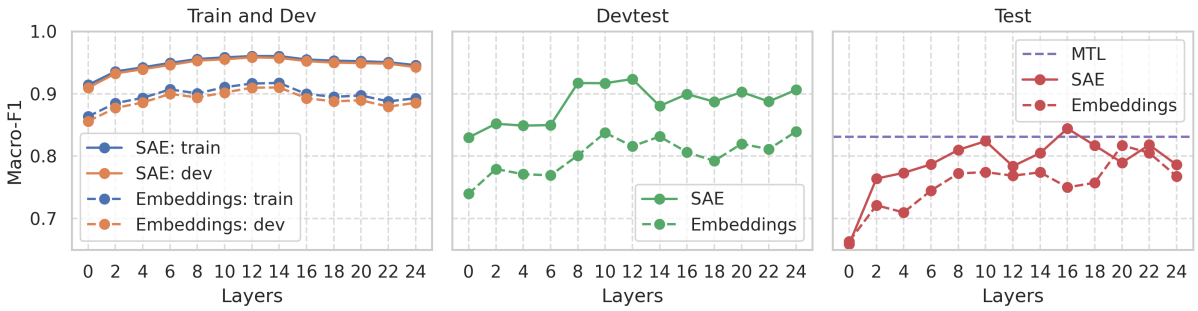

Figure 2: Macro F1 for XGBoost model on mean-pooled activations and SAE-derived features on different subsets of COLING

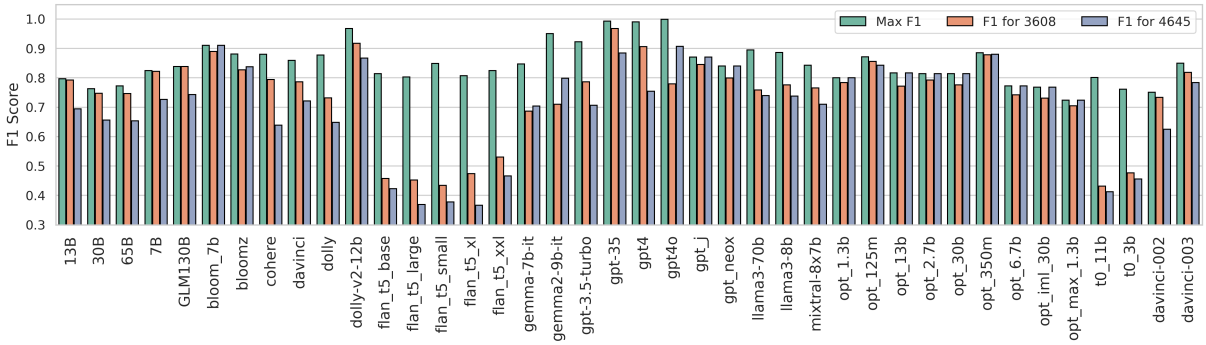

Figure 3: Macro F1 for a threshold classifier on individual features across each model for the 16th layer. Max F1 presents the maximum F1 score for every feature; features 3608 and 4645 are considered general features

are modified as

$$\mathbf{x}' = \mathbf{x} + \lambda A_{\max} \mathbf{d}_i$$

where $\mathbf{x}$ is the original hidden state, $\mathbf{d}_i$ is the column of $\mathbf{W}_{\text{dec}}$ and λ is a scaling factor controlling the steering effect.

Furthermore, we employed the GPT-4o model to analyze changes across all sequences and determine the nature or function of a particular hidden feature (see Appendix I).

4 Results

General Detection Quality. To verify that SAE-derived features enable the detection of artificially generated texts, we apply XGBoost on these features and compare the results with XGBoost applied to mean-pooled activations from the layers. For training, we use the Train Subset of COLING datasets, while testing is conducted on all remaining data from it.

As shown in Figure 2, both SAE features and activations perform well on this subset but degrade slightly on others. Notably, SAE features outperform activations both in training and across other subsets, suggesting that removing superposition helps the classifier focus on more fundamental, atomic features.

Although our primary objective is interpretability, it is worth noting that at the 16th layer SAE-derived features outperform the state-of-the-art MTL model on this dataset (Gritsai et al., 2025). However, out-of-domain performance appears to be influenced by the choice of architecture and model. We conducted additional experiments using other pretrained SAEs based on LLaMA-3.1-8B (He et al., 2024) and Pythia-160M-deduped[3]. While these models demonstrated comparable performance on in-domain tasks, their ability to generalize to unseen domains was noticeably weaker (see discussion in Appendix G).

Domain/Model-Specific and General Features. In our analysis of the feature structure, our objective is to distinguish between general features and domain- or model-specific features. We focus on the 16th layer, as its features have proven to be the most expressive and lead to the best generalization, as discussed in the previous section. Given the highly imbalanced distribution in the dataset, we split it into subsets by domains or models. Then we trained a threshold classifier $\mathbb{I}_{\tau^*}$ for each feature across different subsets and analysed their performance. However, we observed that in most cases,

[3] https://github.com/EleutherAI/sparsify

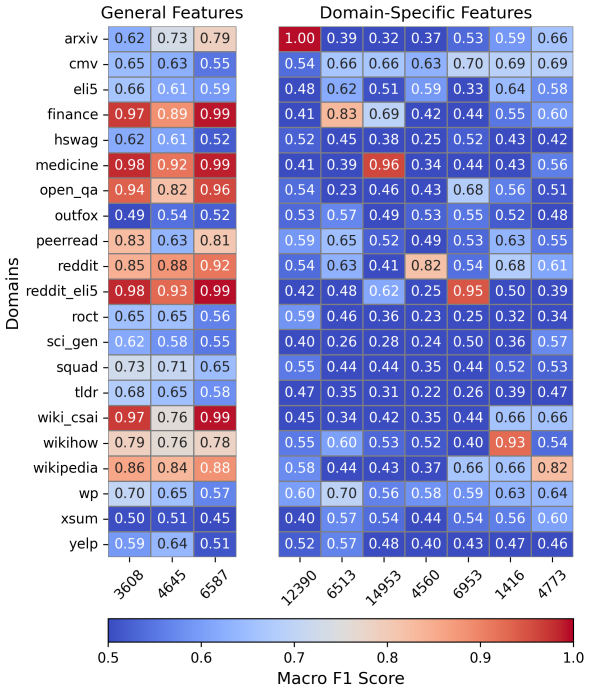

Figure 4: F1 Macro by the domains subsets for some general and domain-specific features for the 16 layer.

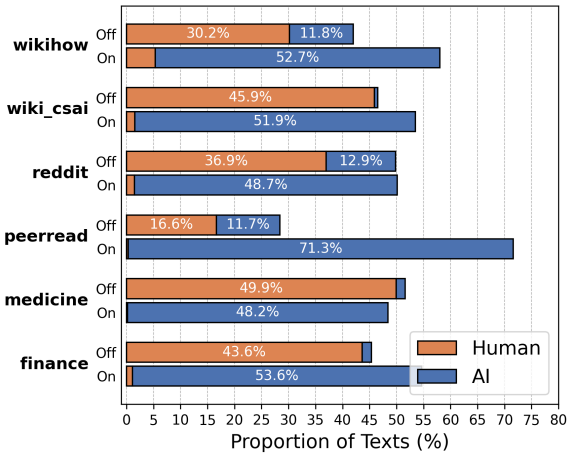

Figure 5: Activation frequency of Feature 3608 in the 16th transformer layer across domains, based on the $\mathbb{I}_0$ classifier. Bars indicate the proportion of texts in which the feature is activated ("On") or not activated ("Off") for Human- and AI-generated texts.

the $\mathbb{I}_{\tau^*}$ is similar to classifying based on $\mathbb{I}_0$, which corresponds to *activation* of specific feature in the text (see discussion in Appendix F and Table 7).

Interestingly, some features consistently exhibit high classification quality across multiple domains or models, which we refer to as **general features**. Some general features (e.g., 3608 and 4645 in layer 16) appear universal across domains and models. To demonstrate this, we compare the best feature for detecting each generator with these universal features (Figure 3). The graph shows that for older models (e.g., Flan, T0), general feature performance drops below random, while the *OPT* family is the most "universal". This suggests distinct characteristics among model classes (see Section 5): older/weaker models (Flan, T0), more advanced LLMs (OPT, Bloom, GPT_J, GPT_Neo), and modern families (GPT-3.5+, LLaMA, Gemma). We also explore how these features behave on different domains in Figure 4. These features achieve high scores across diverse textual domains (e.g., finance, medicine, open-domain QA), suggesting that general features may exhibit more universal linguistic properties.

These features also present the case where, for the majority of domains, classification is effectively equivalent to whether the feature is activated or not, as illustrated in Figure 5. As a result, classification performance is not particularly sensitive to the choice of threshold. Additional results for more features and classification results across different domains are provided in the Appendix E.

In contrast, other features are more specialised, performing well only within specific domains or detecting generations of a particular subset of models, highlighting their domain- or model-specific nature. Examples of these features and their performance are also shown in Figure 4.

Robust Feature Analysis. Building on Kuznetsov et al. (2024), we evaluate the classifier for the presence of harmful superficial features and those vulnerable to different types of attacks on artificial text classifiers, using the RAID dataset. Technical details of these experiments can be found in Appendix D. There, we show that some SAE features can act as indicators of spurious text properties and adversarial attacks that may mislead ATD. In the same time, the features most susceptible to attacks and shallow text properties overlap minimally with those identified as important by XGBoost. Specifically, features 8689 (detecting the GPT3.5+ family) and 14919 (detecting the Bloom family) are very sensitive to sentence length; feature 14919 is also affected by syntactic anomalies in the text, such as unusually long ellipses. Meanwhile, other types of distraction have limited impact on key features.

5 Important Features Interpretation

In this section, we discuss the insights from analyzing feature interpretations, starting with the most robust features: 3608, 4645, 6587, 8264, and

14161. Their performance in the ATD task across various domains and models is shown in Figures 4 and 8.

Strong activations of these features correlate with common LLM-generated text characteristics, such as excessive complexity (3608), assertive claims (4645), wordy introductions (6587), repetition (8264), and formality (14161). These features perform well on GPT3.5+ and other modern LLMs such as LLaMA and Gemma, especially for domains such as finance, medicine, and Wiki-CSAi. However, texts from arXiv are less distinguishable, suggesting GPT models mimic scientific writing more closely.

Feature 8264 stands out with near-perfect performance for GPT3.5+, controlling the conciseness vs. repetition of concepts. Older models lack this feature, leading to lower detectability.

Domain-specific features include overcomplicated syntax (arXiv, feature 12390), excessive details (finance, feature 6513), speculative links (Reddit, feature 4560), and hallucinated facts (Wikipedia, feature 4773). Improper tone (medicine, feature 14953) also signals machine-generated texts.

The most challenging domains for detection are Outfox (essays) and Yelp (reviews), where models mimic human-like writing. This suggests that general "overcomplexity" of the features may not be effective when models are instructed to avoid such traits.

Appendix H provides additional details on the interpretation of the most expressive features. In particular, Tables 8, 9, 10, and 11 present detailed explanations - derived from manual analysis, standard auto-interpretation technique, and auto-interpretation of steering results - for key features, along with examples of texts showing their highest activations. Note that in steering, we adjust a feature's value across all tokens, while in real texts, it activates on only a few. Namely, we observe three activation patterns: token-level (e.g., missed formulae, feature 1416), structural (e.g., sentence endings, introduction words, numbering, feature 6587), and discourse-level (e.g., concept flow, reformulations, contradictions, features 4645, 8689). Tokens where the feature is activated are highlighted in green in the Tables. Manual inspection of documents with high feature values offers complementary interpretative insights.

6 Conclusion

Our analysis shows that modern LLMs often generate easily detectable text due to specific writing styles, such as long introductions, excessive synonym substitution, and repetition. However, adversaries can bypass these features by using less formal and more personalized prompts, leading to more human-like outputs.

Unlike previous approaches, we perform a multifaceted analysis of features for Artificial Text Detection (ATD). We select key features, examine their behaviour across domains and generators, and interpret them both through manually analysing extreme values and inspecting medium shifts with steering and LLM interpretation. This approach provides deeper insights into feature meanings. For example, our interpretation of feature 3608 contrasts with Neuropedia's very specific view, which links it to "tokens associated with mathematical expressions". Similarly, feature 4645, described by Neuropedia as related to "keywords on diabetes" is more broad and relevant in our analysis.

We conclude that Sparse Autoencoder-based analysis of ATD datasets is a valuable tool for understanding text generators, detectors, and how detectors generalize to new setups. Our findings highlight that detecting AI-generated text is easier with a default prompt but becomes difficult when prompt style changes, a crucial consideration for ATD developers.

7 Limitations

Artificial text detection (ATD) is a highly complex and evolving task. With new LLMs emerging almost every month, it is difficult to predict how our method will perform on future artificial text generators. Additionally, novel attack strategies continue to appear, and our approach covers only a subset of them.

Some of the features extracted by the Sparse Autoencoder remain challenging to interpret, as not all exhibit clear or consistent semantic meaning. Several factors may contribute to this difficulty. One possible explanation is that SAE architectures are still relatively new in this context and not yet fully understood. Prior work suggests that SAEs may still contain polysemantic features (Leask et al., 2025), and phenomena such as feature absorption may occur (Chanin et al.), both of which complicate interpretability. It is likely that further research will yield clearer explanations of these features.

Moreover, this short paper focuses exclusively on a single SAE trained on the residual stream of Gemma 2-2B. While we conducted preliminary experiments with other SAEs (such as LLaMA Scope and the Pythia SAE) these were not explored as comprehensively as the SAE for Gemma. Future work should extend this analysis to a broader range of SAEs and language models, which may reveal new types of features and yield deeper insights into artificial text detection.

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A Related Work

Machine-Generated Text Detection. Detection systems for distinguishing human and AI-generated text follow two main approaches: Training-Based and Zero-Shot methods. Training-based approaches fine-tune Transformer models on labeled

datasets for strong in-domain performance (Chen et al., 2023; Li et al., 2023; Yu et al., 2023). In contrast, zero-shot methods analyze statistical patterns without supervised fine-tuning, like token likelihoods, probability curvature or intrinsic dimension (Gehrmann et al., 2019; Mitchell et al., 2023; Tulchinskii et al., 2023).

However, the challenge of making AI-generated text more interpretable for humans has only been addressed by a limited number of approaches, either through manual analysis (Guo et al., 2023) or only partially investingating the dependencies (Kuznetsov et al., 2024).

Sparse Autoencoders and Interpretability. LLM interpretability is especially challenging due to polysemanticity, where a single neuron encodes multiple unrelated concepts (Elhage et al., 2022a, 2023). Sparse Autoencoders (SAEs) were proposed to help isolating more interpretable latent dimensions (Sharkey et al., 2023). Unlike standard autoencoders, SAEs introduce a penalty (e.g. L_1 regularization) to ensure that only a small subset of neurons is active per input, resulting in highly interpretable features (Cunningham et al., 2023).

Recent approaches use large language models or heuristics to automate hypothesis generation and refinement (Bricken et al., 2023; Cunningham et al., 2023; Gao et al., 2023). For example, (Bricken et al., 2023) employ GPT-4 to label sparse dimensions based on top-activating tokens, while (Cunningham et al., 2023) use heuristic methods like measuring overlap with linguistic categories to infer dimension meanings. In our work we employ both manual and automatic interpretation to ensure unbiasedness of our approach.

To the best of our knowledge, Scher (2024) presents the only attempt at explicitly using SAEs for AI-generated text detection. In this preliminary study, SAE trained on toy GPT-2 Small model was used to show that linear probes on SAE activations can modestly outperform baseline detectors. While some neurons were found interpretable, the analysis remained limited in scale and depth. In contrast, our work applies SAEs to a larger model and offers a substantially more comprehensive evaluation, including cross-domain experiments, with richer interpretability and performance analyses.

Datasets and Benchmarks. AI text detection includes many datasets, starting with GPT-2 Output (Solaiman et al., 2019) and Grover (Zellers et al., 2019), as well as TuringBench (Uchendu et al., 2021), which unifies 19 models for cross-evaluation. Additionally, domain-specific corpora and "in-the-wild" tests, such as (Chakraborty et al., 2023), become useful for enhancing model robustness. However, some datasets with AI-generated content may oversimplify the problem for detectors by making AI texts "too detectable" (Gritsai et al., 2024).

B RAID dataset: additional details

"Misspelling" attack	**No attack**
I'm currently gold 2 in rocket league and the **freind** I play with is diamond 2, and he plays the game a lot. I have a busier schedule than him so I **cant** put in the same hours, and whenever I have time to hop on he wants to play. He's my best **freind** so I like talking w him and playing, but I'm getting carried in every match. [...]	This paper presents the second part of our study on multicell coordinated beamforming with rate outage constraints. We propose efficient approximation algorithms to address the non-convex and NP-hard problem of minimizing the total transmission power in a multicell system. [...]

Table 1: GPT-4 generations from RAID with and without attacks. "Attacked" tokens are **highlighted**.

RAID dataset contains generations of numerous models, such as GPT-2-XL (Radford et al., 2019), davinci-002[4], ChatGPT (Schulman et al., 2022), GPT-4 (OpenAI, 2024a), Cohere[5], Mistral 7B (Jiang et al., 2023), MPT-30B[6] and LLaMA (Touvron et al., 2023). However, for our purposes we used only the most powerful ones: ChatGPT and GPT-4.

Authors experimented with two types of decoding (greedy and sampling) and applied repetition penalty to a half of generations. Also they applied various types of attacks to the texts, such as:

- **Alternative spelling** (British)
- **Article** ('the', 'a', 'an') **deletion**
- **Adding paragraph** (`\n\n`) between sentences
- Swapping the case of words from **upper** to **lower** and vise versa

[4] https://platform.openai.com/docs/models
[5] https://docs.cohere.com/docs/models
[6] https://www.databricks.com/blog/mpt-30b

- **Zero-width space**: Inserting the zero-width space U+200B every other character
- Adding **whitespaces** between characters
- **Homoglyph**: Swapping characters for alternatives that look similar
- Randomly shuffling digits of **numbers**
- Inserting common **misspellings**
- **Paraphrasing** with DIPPER (Krishna et al., 2023)
- Replacing words with **synonyms**.

The dataset contains 2,000 continuations for every combination of domain, model, decoding, penalty, and adversarial attack in total. However, for our purposes, we used only 100 continuations for every combination. Table 1 present examples of GPT-4 generations from RAID dataset with and without an attack for comparison.

C COLING dataset: additional details

The COLING dataset contains generations of the models from the following families: a) LLaMA, 7 - 65B (Touvron et al., 2023); b) LLaMA 3, 8 and 70B (Grattafiori et al., 2024); c) GLM, 130B (Zeng et al., 2023); d) Bloomz and Bloom 7B (Muennighoff et al., 2023); e) Cohere[7]; f) GPT 3.5 series, including davinci 001-003 model[8] and gpt-3.5-turbo (Schulman et al., 2022); g) GPT-4 (OpenAI, 2024a) and GPT-4o (OpenAI, 2024b); h) T5-based (Xue et al., 2021) and T0-based (Sanh et al., 2022) models; i) Gemma 7B (Team, 2024b) and Gemma 2, 9B (Team, 2024a); j) GPT-J, 6B (Wang and Komatsuzaki, 2021) and GPT-Neo-X, 20B (Black et al., 2022); k) Mixtral 8 x 7B (Jiang et al., 2024); l) OPT, 125M - 30B (Zhang et al., 2022).

After analyzing the dataset manually, we identified that some samples contain anomalous punctuation, while the others sample from the same models (or human texts) were normal and did not contain without these anomalies. We gathered some examples of such inconsistencies in Table 3. We hypothesize that this inconsistency arises from the COLING dataset being composed of multiple datasets created by different authors.

Previous research works have shown that spurious features related to the text length (Kushnareva et al., 2024) and formatting (Dugan et al., 2024) significantly affect artificial text detection. Moreover, Cai and Cui (2023) found that sometimes adding even a single space before the comma may confuse detectors. Thus, we find it important to analyze the peculiarities of the dataset we use and investigate whether the features we examine truly reflect inherent properties of the generated texts or are simply influenced by superficial traits.

[7] https://docs.cohere.com/docs/models
[8] https://platform.openai.com/docs/models

Pattern	Layer 16	18	20
Length	1033, **16028**	7373	8684
␣,␣	-	2199	6631
....	2889, 8689, **14919**	3851, **12685**, 16302	**8573**, 11612, 12748
\n ,	**14919**, **16028**	**12685**	**8573**, 12267

Table 2: Features, that are the most sensitive to the length of samples and syntactic anomalies

Figures 6a and 6b illustrate the frequency of various anomalies across the model generations. In particular, we found that GPT-NeoX generations contain the "...." anomaly most frequently among all models. Meanwhile, human-generated texts in the COLING dataset commonly contain spaces before commas or commas after line breaks, which is likely a side effects of preprocessing procedures applied when the datasets were compiled. Additionally, we discovered that the GPT-4o model used double line breaks in almost every text it generated; models from the Gemma and LLaMA-3 families displayed double line breaks in more than half of their generations as well. In contrast, human texts contained far fewer double line breaks, with occurrences of three or more line breaks being relatively rare across all models.

Talking about the lengths of the samples, we see that they also vary a lot (see Figure 7). In particular, T5- and T0- based models tend to generate much shorter texts than other models. Due to this, we investigate further which features are the most sensitive to the length of the input texts and syntactic anomaly in the Appendix D.

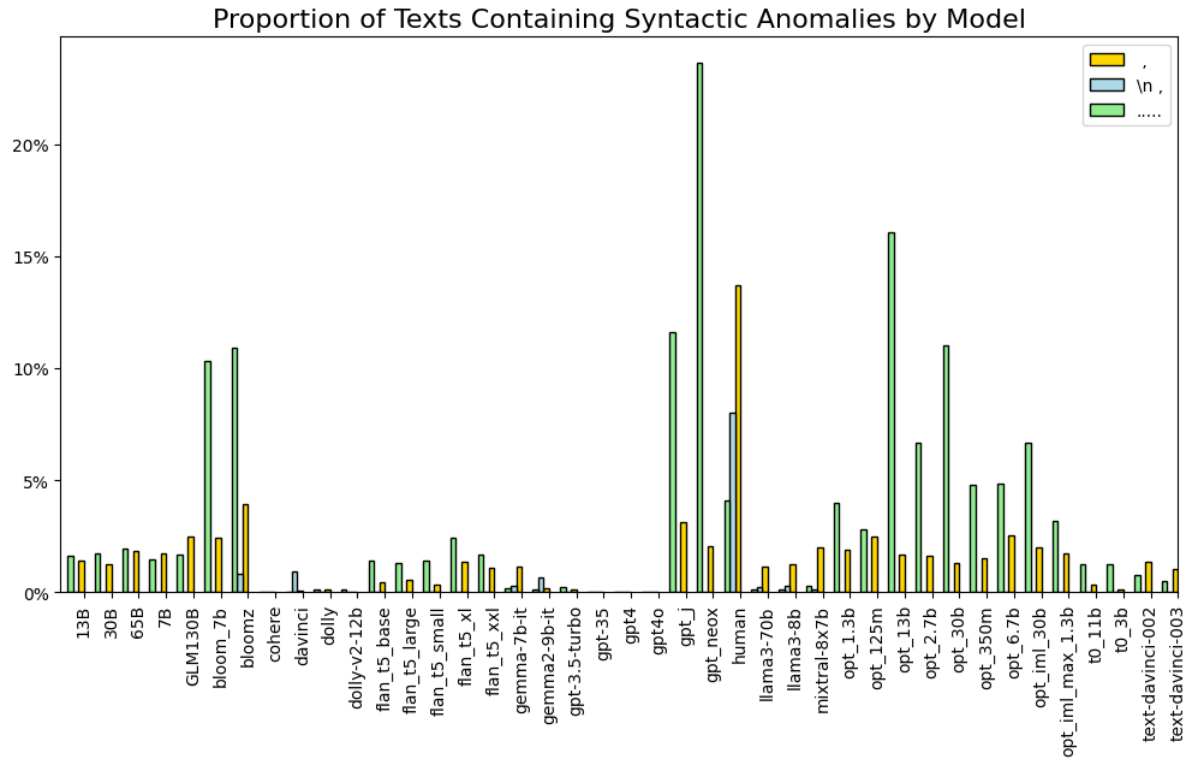
D Isolating features most sensitive to the length of samples, syntactic anomalies and attacks

To identify the features that are the most sensitive to particular peculiarities of the texts, we took measures to isolate influence of those peculiarities from other text properties, such as the style or topic. To achieve this, we performed the algorithms de-

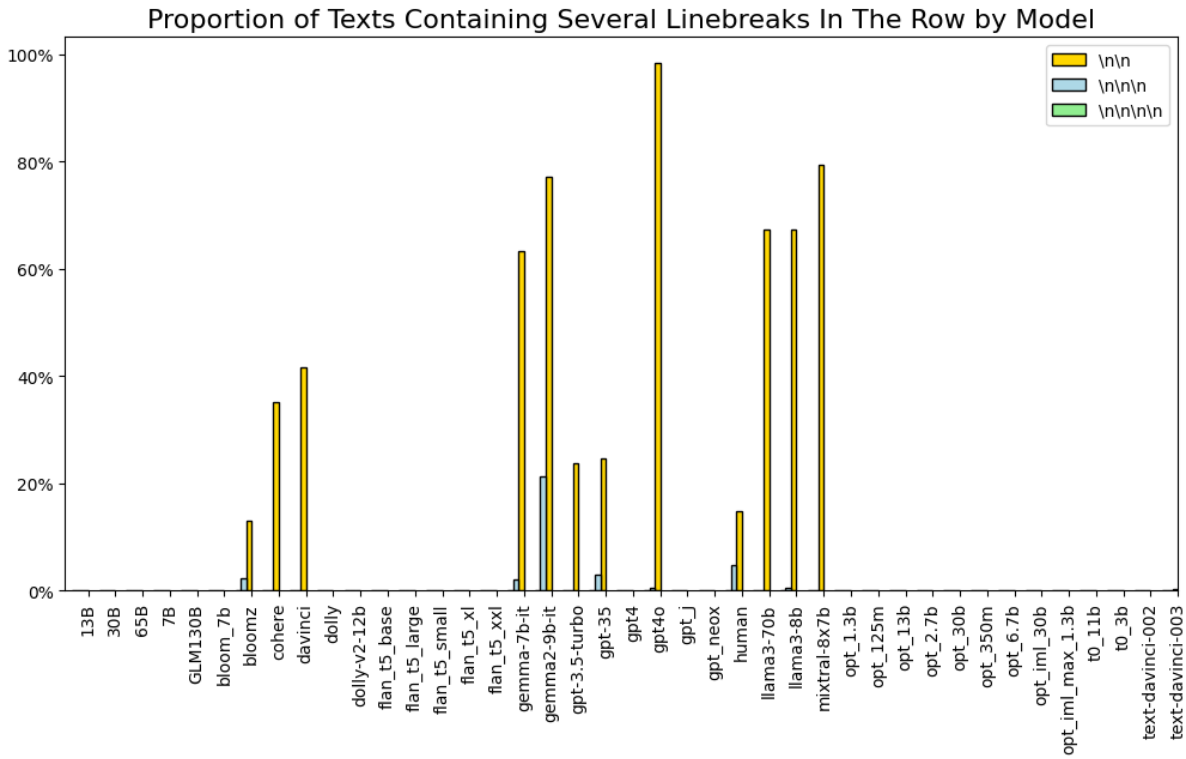
LLaMA 3-70B generation fragment (line breaks highlighted with red)
Hold it there with that hand while your other hand moves the bandage around your knee. Wrap it all the way around once until the wrap comes around to meet the loose end. Pull it snug to secure it. **\n \n \n \n \n \n \n \n \n** Make sure to wrap over the end you started with and put a twist (or two, so that the roll returns to its original position) in the bandage directly above the end to hold it in place.
LLaMA 3-70B generation fragment (normal punctuation)
Either use your fingernails or a pair of pliers to secure the stud by folding down the spike ends on the inside of the shoe. Repeat this process for all of the studs.
LLaMA 7B generation fragment (anomalous spaces before punctuation highlighted with red)
I just learned about broiling recently␣␣,␣␣but let 's talk about baking first␣␣.␣␣When you bake␣␣,␣␣you cook the food by surrounding it with hot air␣␣.␣␣Because the hot air is all around the food␣␣,␣␣the food cooks from all the sides␣␣.␣␣If you use a toaster oven␣␣,␣␣you 'll notice that the heating elements are not really on when you bake␣␣.␣␣
LLaMA 7B generation fragment (normal punctuation)
This place is average at best. Our meal was a mixed bag of good and bad. On the good side, took our reservations and when we showed up on time we were promptly seated. Also, they had a very nice Carpaccio appetizer. That was well done. That was it.... no more good. On the bad side, all of the dinners were rather bland and tasteless. My wife's lamb chops were nothing to write home about.
OPT 30B generation fragment (long ellipses highlighted with red)
His wife. God **.....** she was always so beautiful. We met at college, you see. The only woman I ever loved. And boy did I love her. [...] All the media knew he was a jack-ass, but she **.....** she was made for the campaign trail.
OPT 30B generation fragment (normal punctuation)
The first time I went there a couple of years ago, it was pretty good. Then I went there a year ago and it was ok. Went again tonight and in my opinion, it was some of the worst food I have ever had. Like others have said, very inconsistent but either way, I won't be going back.

Human text fragment (line breaks before commas highlighted with red)
, After scrubbing, allow the tattoo to sit for two hours without washing the salty scrub off. Once the two hours are up, you should wash it thoroughly with cold water for 5-10 minutes. You may notice some ink being washed away as the area is rinsed with water[...] It is also advisable to apply a small amount of vitamin E over the area as this helps to promote healing and prevent the formation of a scar. Vitamin E also helps to reduce inflammation and pain. **,** Use a clean hand cloth to dry the skin and then an antibiotic cream can be applied on top. Use sterile gauze to cover the area, which can be held in place using tape from a first aid kit. This helps to protect the area and prevent infection. **,** The dressing can be taken off after three days and the area assessed. If the skin is painful or reddened, it may be infected. If this is the case, it is advisable to see the doctor or visit the nearest hospital.
Human text fragment (normal punctuation)
St Clare's Catholic Primary School in Birmingham has met with equality leaders at the city council to discuss a complaint from the pupil's family. The council is supporting the school to ensure its policies are appropriate. But Muslim Women's Network UK said the school was not at fault as young girls are not required to wear headscarves. Read more news for Birmingham and the Black Country. The Handsworth school states on its website that "hats or scarves are not allowed to be worn in school" alongside examples including a woman in a headscarf. Labour councillor Waseem Zaffar, cabinet member for transparency, openness and equality, met the school's head teacher last week. In a comment posted on Facebook at the weekend, claiming the school had contravened the Equality Act, the councillor wrote: "I'm insisting this matter is addressed asap with a change of policy."

Table 3: Machine- and human-generated text samples from COLING25 with various punctuation patterns. Anomalies are marked in red.



(a) Frequency of occurrence of three common syntactic anomalies — spaces before commas, commas after line breaks, and ellipses with more than three dots in the texts, generated by different models. The y-axis represents the percentage of samples from COLING in which each anomaly appears *at least* once, while the x-axis indicates the generation models.



(b) Frequency of occurrence of the excessive line breaks — namely, two, three, or four line breaks in a row. The y-axis represents the percentage of COLING dataset samples in which each amount of excessive line breaks appears at least once, while the x-axis indicates the generation models.

Figure 6: Syntactic anomalies and excessive line breaks in model-generated texts.

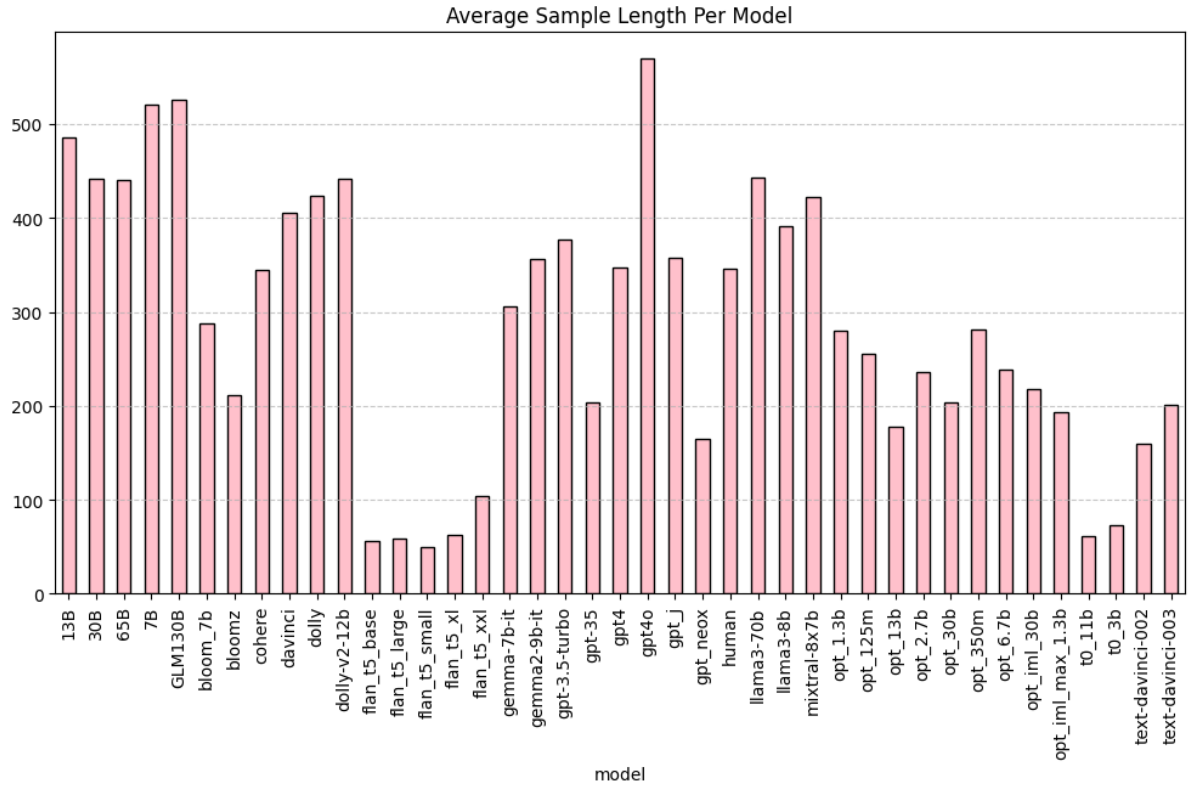


Figure 7: Average length of the text sample in COLING dataset by the generation model. The vertical axis represent the text length (measured in Gemma-2-2B tokens), the horizontal axis indicates the generation models.

scribed below.

D.1 Length

To identify features most sensitive to sample length, we used human-written texts from the COLING dataset, since ir contains a significantly larger proportion of human texts compared to model-generated ones, and these texts are much more diverse. Then, we selected those domains of human texts that contain a sufficiently large amount of text samples (> 1000 samples). For each such domain, we identified the top 10% longest and top 10% shortest texts. For both sets, we calculated the values of each feature, then computed the difference between the average feature values for the longest and shortest texts. Thus, for each domain, we identified the top-10 features with the greatest differences. Subsequently, we computed the intersection of these top-10 features across all domains, to eliminate the influence of properties of each particular domain.

D.2 Syntactic anomalies

For each syntactic anomaly, we identified the top three domains of human texts from COLING that contained the highest proportion of texts exhibiting the given anomaly. For each domain, we calculated average feature values for texts with and without the anomaly. Then, we selected top-10 features with the greatest differences for each domain. Finally, we computed the intersection of these top-10 features across all top-3 domains, isolating those features that consistently exhibited the highest sensitivity to the given anomaly. The process was repeated for several layers of SAE.

The results are presented in the Table 2 for length and three described earlier anomalies: spaces before commas, commas after line breaks, and ellipses with more than three dots in the texts.

As one can see, the most anomalies persistently activate from 1 to 3 SAE features on each layer. At the same time, this method didn't reveal any features persistently sensitive to markdown paragraphs (##) and to repeating line breaks (\n\n). Interestingly, we identified several features that reacted to markdown paragraphs by hand (for example, features 1033 and 15152 on the 16th layer of SAE). However, the fact that these features were not captured by our algorithm suggests that they lack sufficient stability under domain variation.

Only features 8689 and 14919 from Table 2

are among the best in detecting GPT models and Bloom model families respectively (Table 10).

D.3 Attacks

To identify features most sensitive to attacks, we switched to the RAID dataset. From this dataset, we selected three of the most powerful generating models: ChatGPT-3.5, GPT-4, and human. For each model and domain, we calculated the top-10 features that are the most sensitive to each type of attack, using the same method as for syntactic anomalies. Then, for each attack, we took the intersection of the top-10 features across all domains and generation models. The results are presented in the Table 4.

As one can see, the Table doesn't include "number", "paragraphs insertion", "alternative spelling", "misspelling" and "paraphrase" attacks. This is so because our method didn't find the features that would indicate these types of attack consistently across all models and domains. Also note that this time, we calculated the top-10 features not from all available features but from the top 10% most important features for ATD based on XGBoost results. If we calculate the top-10 from all possible features, our strict method don't capture any intersections.

The selected feature set does not intersect with the best ATD detection features, whether general or model- or domain-specific. A detailed analysis of how each of the top-performing ATD detection features individually responds to adversarial attacks deserves further investigation but is beyond the scope of this work.

E Cross-domain analysis

Tables 5 and 6 show the cross-domain performance of threshold-based classifiers $\mathbb{I}_{\tau^*}$ for two representative general features (3608 and 6587) of 16th layer. These results support our claim that classifiers built on such features are largely domain-invariant. Regardless of the domain used for training, the classification performance remains consistently high across test domains.

In Figure 8, we report the macro F1 score for the classifiers built upon the most distinctive general and model-specific features extracted from the 16th layer. The top features across domain and model subsets are shown in Figures 9 and 10, respectively.

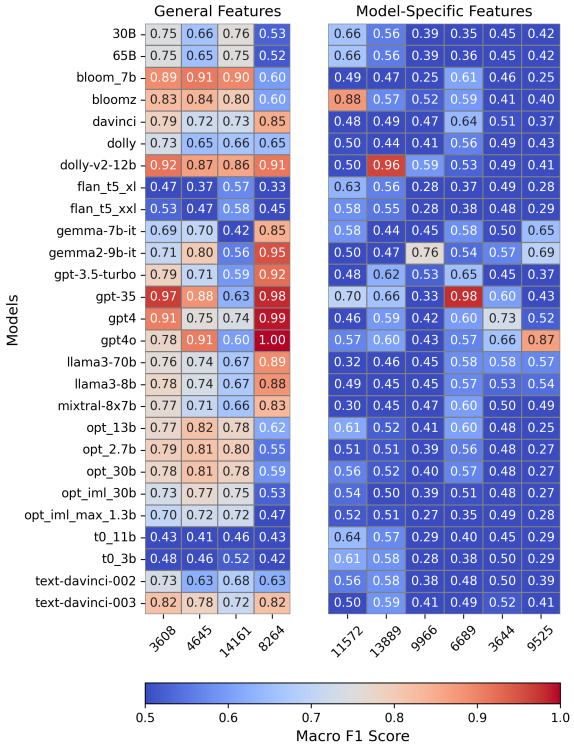


Figure 8: F1 Macro by the models subsets for some general and model-specific features for the 16 layer

F Threshold Classifiers Analysis

To further investigate the role of individual feature activations in classification performance, we compared $\mathbb{I}_{\tau^*}$ and $\mathbb{I}_0$ on general features.

Table 7 summarizes the performance of these classifiers across various domains. We find that classifier $\mathbb{I}_0$, which only checks for activation, performs comparably to (and sometimes better than) the threshold-tuned classifier $\mathbb{I}_{\tau^*}$. In particular, for feature 4645, the performance gap is significant in favor of $\mathbb{I}_0$ across nearly all domains.

These results suggest that in many cases, the activation of a specific feature is already a strong signal for classification, reinforcing the interpretability and simplicity of using feature activation as a decision rule.

G Results on other LLMs

We conducted similar experiments on other SAE, the first is based on LLaMA 3.1 8B, namely LLaMA-Scope (He et al., 2024). Another SAE is based on Pythia-160M-deduped. The results are presented on Figures 11a and 11b. For these two experiments, we did not train on Train set, as for LLaMA Scope it was too computationally expensive, therefore we trained XGBoost only on Dev,

Layer	Art. deletion	Homoglyph	Whitespace	0-width space	Upper/lower	Synonim
16	3518, **13998**	**9266**	**9266**, 5627, 10229, 750	**9266**, 10262	**13998**	4052, 9100, **13998**
18	7905, **2006**	8408, 4859, **3037**	281, 1970 15780	281, 12530 4859	**3037**, **2006**	1642, **2006**, 13017, **3037**, 10815
20	**11612**	15523, 9589, 743	12602, 11363, 15415, 3879	6793, 9589	**11612**, 3302	**11612**

Table 4: Features that are the most sensitive to various types of attacks

Train Set	Finance	Medicine	PeerRead	Reddit	Wiki-CSAI	Wikipedia	WikiHow	OpenQA	ArXiv
All	0.97	0.98	0.78	0.82	0.97	0.83	0.82	0.92	0.57
Finance	0.97	0.98	0.77	0.82	0.97	0.83	0.81	0.92	0.57
Medicine	0.97	0.98	0.83	0.85	0.98	0.86	0.82	0.94	0.62
PeerRead	0.97	0.98	0.83	0.85	0.98	0.86	0.82	0.94	0.62
Reddit	0.97	0.98	0.81	0.85	0.98	0.85	0.82	0.93	0.61
Wiki-CSAI	0.96	0.97	0.75	0.80	0.97	0.81	0.81	0.91	0.55
Wikipedia	0.97	0.98	0.82	0.85	0.98	0.86	0.82	0.94	0.62
WikiHow	0.94	0.92	0.67	0.75	0.94	0.75	0.79	0.85	0.49
OpenQA	0.97	0.98	0.82	0.85	0.98	0.86	0.82	0.94	0.62
ArXiv	0.97	0.98	0.83	0.85	0.98	0.86	0.82	0.94	0.62

Table 5: Cross-domain performance of threshold classifier $\mathbb{I}_{\tau^*}$ for Feature 3608 in 16th layer. All represents combined data of all domains in Train Set. Green indicates better or same performance as in All row; red indicates performance below it.

Train Set	Finance	Medicine	PeerRead	Reddit	Wiki-CSAI	Wikipedia	WikiHow	OpenQA	ArXiv
All	0.99	0.99	0.77	0.90	0.99	0.88	0.79	0.93	0.77
Finance	0.99	0.99	0.81	0.91	0.98	0.89	0.78	0.96	0.79
Medicine	0.99	0.99	0.77	0.90	0.99	0.88	0.79	0.94	0.77
PeerRead	0.99	0.99	0.81	0.91	0.98	0.89	0.78	0.96	0.78
Reddit	0.99	0.99	0.81	0.92	0.98	0.89	0.78	0.96	0.79
Wiki-CSAI	0.98	0.99	0.70	0.87	0.99	0.87	0.78	0.84	0.72
Wikipedia	0.99	0.99	0.78	0.90	0.99	0.88	0.79	0.94	0.78
WikiHow	0.99	0.99	0.71	0.88	0.99	0.87	0.78	0.86	0.73
OpenQA	0.99	0.99	0.82	0.92	0.97	0.89	0.77	0.96	0.79
ArXiv	0.99	0.99	0.82	0.92	0.97	0.89	0.77	0.96	0.79

Table 6: Cross-domain performance of threshold classifier $\mathbb{I}_{\tau^*}$ for Feature 6587 in 16th layer. All represents combined data of all domains in Train Set. Green indicates better or same performance as in All row; red indicates performance below it.

and tested on Devtest and Test subsets.

The out-of-domain results are lower compared to those obtained using Gemma-based SAE features and activations. We attribute this performance gap to two primary factors: (a) the smaller training dataset used in these particular experiments, which may have limited the model's ability to learn generalized features, and (b) the possibility that the classifiers based on Pythia and LLaMA focus more heavily on specific features, leading to overfitting. Additionally, the narrower performance gap between SAE features and embeddings in Pythia, compared to Gemma and LLaMA, is likely due to Pythia's relatively smaller model size and its reduced capacity to retain useful information within its embeddings.

Classifier		Finance	Medicine	PeerRead	Reddit	Wiki-CSAI	Wikipedia	WikiHow	Open-QA	ArXiv
3608	$\mathbb{I}_{\tau^*}$	0.97	0.98	0.80	0.84	0.98	0.84	0.82	0.93	0.59
	$\mathbb{I}_0$	0.97	0.98	**0.83**	**0.85**	0.98	**0.86**	0.82	**0.94**	**0.62**
4645	$\mathbb{I}_{\tau^*}$	0.74	0.71	0.44	0.86	0.65	0.79	**0.78**	0.59	0.56
	$\mathbb{I}_0$	**0.92**	**0.92**	**0.63**	**0.89**	**0.83**	**0.85**	0.63	**0.82**	**0.73**
6587	$\mathbb{I}_{\tau^*}$	**0.99**	**0.99**	0.80	0.91	**0.98**	**0.89**	**0.78**	0.95	0.78
	$\mathbb{I}_0$	0.98	0.98	**0.82**	0.91	0.90	0.87	0.73	**0.96**	**0.79**

Table 7: F1 Macro for $\mathbb{I}_{\tau^*}$ and $\mathbb{I}_0$ classifiers (feature and method) across various domains.

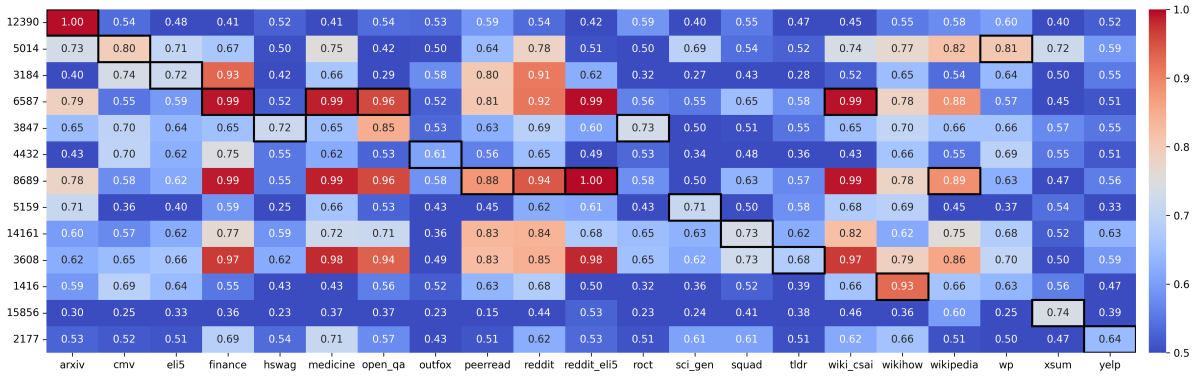


Figure 9: Top features by domains subsets. **Black** rectangles indicite the domain for which the feature is top-1.

H Expressive features interpretations

Let us examine the interpretation results of the most expressive features.

General features. (Table 8)

According to steering-based explanation, all presented features makes text lengthy and overwinded, but with different flavour: feature 3608 increases sentence complexity, feature 4645 responsible for knowledge presentation complexity (even without real knowledge), and feature 6587 incorages lengthy introductionds and explanations. According the manual analysis, the first of them is concentrated on "scientfically-looking" tokens, the second reacts on factual contradictions, and the third is activated in structural elements of the text, like item labels or introduction words.

GPT-specific features. (Table 9)

In Table 9 we present features detecting well modern LLMs, especially GPT family. Feature 8689 responsible for excessive synonym substitutions, and feature 8264 for thoughts repetitions (by steering interpretation); from the examples we can see that the first is activated on paraphrased ideas already mentioned in the text, or on discussing alternatives. The second is activated on long common words, specific for typical GPT style.

Domain-specific features.(Tables 10, 11)

Feature 12390 (arxiv) is responsible for syntactic complexity. It is activated linking structures typical for scientific writing.

Feature 1416 (wikihow) is interpreted as increasing "phylosofical or metaphorical explanations" instead of being simple and clear. In fact, its extreme values succesfully detects texts where crucial parts are missing, namely, results of parsing errors where formulas and mathematical characters are lost. So, discarding mathematical characters is the extreme case of the unclarity.

Feature 6513 (finance) represent exessive explanations behind clear facts. It is activated on opinionate words and syntactic constructions "I mean", "like" etc

Feature 14953 (medicine) responsible for second-person speech with direct instructions. Activated on phrases containing "You" or "Your" pronouns. Steering interpretes it as change from informal to formal language.

Feature 4560 (reddit) responsible for "speculative casuality", whith Reddit discussions as its extreme implementation

Feature 4773 reacts on words flexibility. Steering interprets it as "hallucinations".

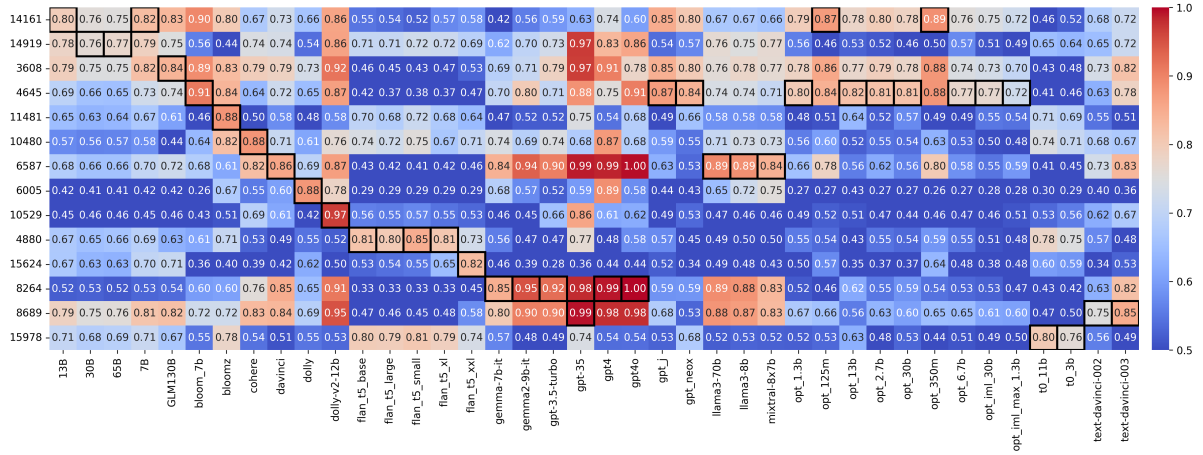
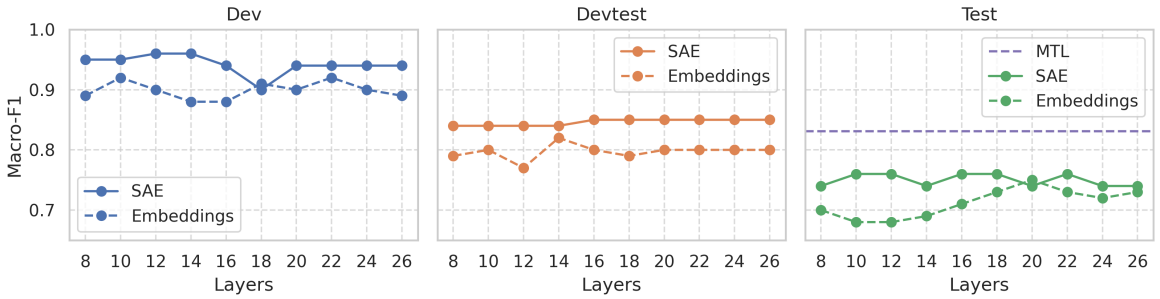
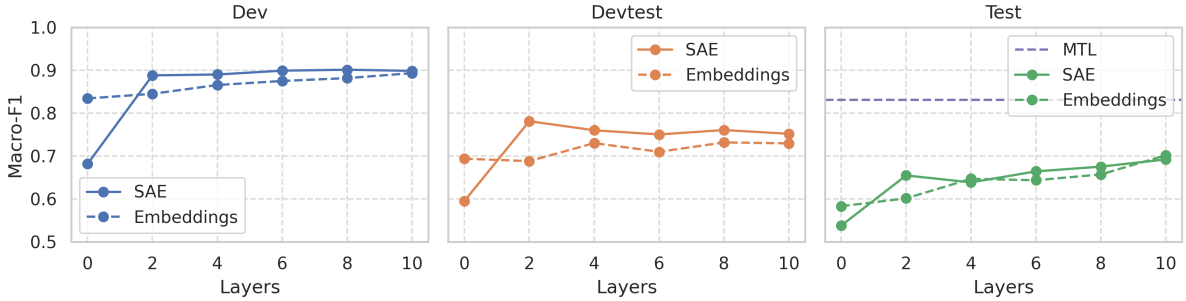


Figure 10: Top features by models subsets. **Black** rectangles indicite the model for which the feature is top-1.



(a) Results for LLaMA Scope



(b) Results for Pythia

Figure 11: Macro F1 for XGBoost model on mean-pooled activations and SAE-derived features on different subsets of COLING for two other SAE-based models

I Steering: additional details and examples

Feature steering was applied using shifts from the following set: $\{-4.0, -3.0, -2.5, -2.0, -1.5, -1.0, -0.5, 0.5, 1.0, 1.5, 2.0, 2.5, 3.0, 4.0\}$. To analyze the effects of these modifications, we utilized the GPT-4o model. The prompt is shown in Figure 12.

In Table 12, we present examples of steering for several features with their GPT-based interpretations using three prompts. While GPT generally captures the influence of the features, some effects are not fully accounted for. For instance, feature 6513 causes unnecessary expansion in factual questions (prompt P2) but adds positive intent in opinionated contexts. Feature 4773 enhances writing sophistication, feature 1416 boosts creativity in fictional contexts and causes hallucinations in factual ones, and feature 14953 turns every response into legal advice.

Manual	ChatGPT	Steering
Feature 3608		
Detects ill-posed characters and words, which should appear normally in scientific context, e.g. numbers, brackets, or words like “n” and “neighbourhood”.	May regulate sentence complexity and readability; Controls whether text is simple or contains complex, nested clauses.	**Affects:** Stylistic & Structural Complexity **Weakening (-2.0 and below)**: Produces short, choppy sentences with minimal subordination. **Neutral (0.5 to 1.5)**: Maintains a natural balance of sentence complexity. **Strong strengthening (2.0 and above)**: Creates overly complex, multi-clause sentences that may be harder to read.
Sum value: 11018.12, domain: wikihow, model: bloomz Here are some tips about what you’ll want to do before graduation: 1) Make sure you graduate! 2) Don’t forget to celebrate! 3) Be prepared for the future. 4) Enjoy yourself. 5) Get excited. 6) Celebrate. 7) Have fun. 8) Graduate. 9) Go to parties. 10) Do whatever. 11) Congratulations. 12) Good luck. 13) See ya. 14) You did it. 15) Happy. 16) 17) 18) 19) 20) 21) 22) 23) 24) 25) 26) 27) 28) 29) 30) 31) 32) 33) 34) 35) 36) 37) 38) 39) 40) 41) 42) 43) 44) 45) 46) 47) 48) 49) 50) 51) 52) 53) 54) 55) 56) 57) 58) 59) 60) 61) 62) 63) 64) 65) 66) 67) 68) 69) 70) 71) 72) 73) 74) 75) 76) 77) 78) 79) 80) 81) 82) 83) 84) 85) 86) 87) 88) 89) 90)		
Feature 4645		
Long “lively” stories with coherent topics, but consisting mainly of common phrases, with too long sentences, hard to capture the objective of the story.	May influence factual confidence and assertion strength; Affects whether statements are presented as speculation or fact.	**Affects:** Semantic & Persuasive Strength **Weakening (-2.0 and below)**: Introduces hedging and uncertainty (e.g., “Some scientists believe that...”). **Neutral (0.5 to 1.5)**: Provides balanced, well-supported claims **Strong strengthening (2.0 and above)**: Encourages assertive, definitive claims, even when speculative (e.g.,“Scientists have proven that...”).
Sum value: 24744.33, domain: wp, model: opt-30b I opened my eyes, expecting to be back in the car crash, hearing the screams of agony and the feeling of twisted metal between my ribs. But instead, I found myself on a bed with... My heart was racing as if it were running away from me. When did that happen? It had been so long since I’d considered what happened after death— but now here I lay, staring up at nothingness above me ; empty black sky and flickering lights danced around me like fireflies in a dark forest . My body felt heavy and weighted down by an unseen force all over again . "Who are you ?"		
Feature 6587		
Detects numbered lists or other well-structured stepwise reasoning text	May regulate directness vs. explanatory buildup; Affects whether information is presented concisely or with extended context.	**Affects:** Stylistic & Informational Density **Weakening (-2.0 and below)**: Produces concise but sometimes abrupt statements **Neutral (0.5 to 1.5)**: Ensures a balanced level of explanation. **Strong strengthening (2.0 and above)**: Encourages long-winded introductions before getting to the point.
Sum value: 4727.02, domain: wikihow, model: gpt-3.5-turbo Summer vacation is a time to enjoy yourself and make memories that last a lifetime. However, sometimes it can be hard to find ways to stay entertained and not get bored during those long summer days . Luckily, there are plenty of activities you can do to keep yourself busy and have fun at the same time . Here are some ideas to try out : 1. Decorate your room : Give your room a fresh new look by hanging up some posters, re-arranging furniture or adding some colorful throw pillows . 2. Prank call someone : Make some silly phone calls with your friends and see who can come up with the funniest conversation . 3. Stay up all night : Have a late-night movie marathon, play board games, or just stay up talking with friends		

Table 8: Feature interpretations and examples of texts from the COLING dataset with exceptionally high feature values. Tokens where the feature is activated are highlighted in green . Red color highlights the parts of the text that are believed to influence the feature. For example, for feature 4645, the contradiction between the claim and the generated content is emphasized.

Manual	ChatGPT	Steering
Feature 8689, specific for **GPT family**		
Detects long "gpt-style" instructions, too verbose and obvious; highly sensitive to the presense of "...." anomaly	May influence lexical variety and synonym usage; Determines whether text repeats the same words or uses synonyms.	**Affects:** Stylistic & Lexical Diversity **Weakening (-2.0 and below)**: Causes overuse of the same words and phrases. **Neutral (0.5 to 1.5)**: Provides natural variation in word choice. **Strong strengthening (2.0 and above)**: Uses excessive synonym substitution, sometimes making the text sound unnatural.
Sum value: 26528.57, domain: outfox, model: mixtral-8x7b In recent years, online learning has become an increasingly popular alternative to traditional brick-and-mortar education. While there are certainly advantages to attending classes in person, there are also many potential benefits to attending classes online from home, particularly for students who are sick or have experienced bullying or assault . One of the most significant benefits of online learning for sick students is the ability to continue their education without the risk of spreading illness to others.		
Feature 8264, specific for **GPT family**		
Detects long "gpt-style" instructions, too verbose and obvious	May regulate redundancy and reiteration of key points; Controls whether concepts are concisely stated or overly repeated.	**Affects:** Stylistic & Structural Redundancy **Weakening (-4.0 to -2.0)**: Produces underdeveloped explanations lacking reinforcement. **Neutral (0.5 to 1.5)**: Ensures effective reinforcement of key ideas. **Strong strengthening (2.0 and above)**: Introduces excessive repetition, causing sentences to loop around the same idea.
Sum value: 23010.46, domain: wikihow, model: gpt4o Creating a soothing and predictable environment can do wonders for motivating an autistic teen or adult to exercise. Loud noises, bright lights, and chaotic spaces may cause sensory overload, making it difficult for them to focus. An environment that feels secure and calm can greatly enhance their willingness to engage in physical activity. Try choosing outdoor spaces like parks or serene gardens, or opt for quiet times at the gym.		

Table 9: Model-specific SAE-derived features.

Feature 12390, specific for **arxiv** domain		
Activated on linking words in dependent syntactic structures related to research topic discussion.	May influence sentence complexity and syntactic variety; Determines whether text consists of simple or complex sentence structures.	**Affects:** Stylistic & Structural Complexity **Weakening (-4.0 to -2.0)**: Produces short, choppy sentences with minimal subordination. **Neutral (0.5 to 1.5)**: Maintains a natural balance of simple and complex sentences. **Strong strengthening (2.0 and above)**: Creates overly complex, multi-clause sentences, making readability difficult.
Sum value: 4348.42, domain: peerread, model: human This paper proposes an approach to learning a semantic parser using an encoder-decoder neural architecture, with the distinguishing feature that the semantic output is full SQL queries. The method is evaluated over two standard datasets (Geo880 and ATIS), as well as a novel dataset relating to document search .		
Feature 1416, specific for **wikihow** domain		
Detects scientific documents with missed formulas and special symbols (document parsing errors). In normal documents, reacts to abnormal punctuation.	May control abstract reasoning and conceptual depth; Influences how well the model develops abstract ideas or remains concrete.	**Affects:** Semantic & Logical Expansion **Weakening (-2.0 and below)**: Produces simplistic, direct statements without deeper analysis. **Neutral (0.5 to 1.5)**: Allows for balanced explanation of abstract ideas. **Strong strengthening (2.0 and above)**: Encourages philosophical, speculative, or metaphorical expansions, sometimes losing clarity.
Sum value: 3596.64, domain: wikipedia, model: human In mathematics, the Hahn decomposition theorem, named after the Austrian mathematician Hans Hahn, states that for any measurable space and any signed measure defined on the - algebra, there exist two - measurable sets, and , of such that : and .		

Table 10: Domain-specific SAE-derived features - part 1

Feature 6513, specific for **finance** domain		
Detects highly informal and opinionate speech	May regulate factual density vs. elaboration; Affects whether facts are presented concisely or with excessive background detail.	**Affects:** Semantic & Informational Density **Weakening (-4.0 to -2.0)**: Produces brief, surface-level facts without context. **Neutral (0.5 to 1.5)**: Provides balanced factual depth. **Strong strengthening (2.0 and above)**: Introduces unnecessary historical or background expansions.
Sum value: -, domain: reddit, model: llama3-70B And , like, eventually , she built up this whole compiler system from scratch , without even having a compiler to begin with. I mean, that' s just, wow . It' s like , she had to, like, manually translate the assembly code into machine code , which is just , ugh , so much work.		
Feature 14953, specific for **medicine** domain		
Second-person recommendations (legal, medical) in form "You should", "There are restrictions" and etc.	May control formality and academic tone—Determines whether text appears conversational or highly formal.	**Affects:** Stylistic & Tonal **Weakening (-4.0 to -2.0)**: Produces casual, informal language (e.g., "This is super important because..."). **Neutral (0.5 to 1.5)**: Maintains a professional but accessible tone. **Strong strengthening (2.0 and above)**: Introduces highly academic or dense phrasing (e.g., "In accordance with the prevailing theoretical framework...").
Sum value: -, domain: wikihow, model: human Each state has different requirements in order to qualify for a liquor license or permit. You should check to see that you meet those requirements before beginning the application process.		
Feature 4560, specific for **reddit** domain		
Detects signs of informal internet discussions: short 1st person sentences, conjectures, datetime labels (parsing artifacts), words like "Yeah", "Ah".	May regulate cause-effect relationships in historical and scientific explanations; Affects whether relationships between events are clearly established.	**Affects:** Semantic & Causal Coherence **Weakening (-4.0 to -2.0)**: Produces disconnected statements without clear causal links. **Neutral (0.5 to 1.5)**: Ensures logically connected, well-supported cause-effect explanations. **Strong strengthening (2.0 and above)**: Adds exaggerated or speculative causal links (e.g., "The invention of fire directly led to modern civilization.").
Sum value: -, domain: eli5, model: Bloom-30B He's like the hippie-hating version of Greg Proops . This is pretty much the only positive thing I can say about him . posted by crunchland at 6:50 AM on November 17, 201 1 At this point I'm just waiting for the inevitable "Hey guys, I'm a comedian who's got a beef with Occupy" FPP . posted by Aquaman at 6:51 AM on November 17 , 2 011 [1 favorite] This is what happens when you believe your own press.		
Feature 4773, specific for **wikipedia** domain		
The feature emphasizes words that repeat in the text many times in various forms, either morphological (for foreign words), in different languages, or just synonyms. E.g. "Toilet", "Diaper", "Infant pot"; or "Huguteaux", "Hugueois", "Huguenos". The same feature detects hallucinated generations with corrupted words.	May regulate factual consistency and logical flow; Determines whether details remain accurate or become speculative.	**Affects:** Semantic & Logical Consistency **Weakening (-4.0 to -2.0)**: Produces simplistic, repetitive descriptions (e.g., "Mars is red. Mars has an atmosphere."). **Neutral (0.5 to 1.5)**: Ensures well-structured and accurate statements. **Strong strengthening (2.0 and above)**: Encourages hallucinated details and speculative claims (e.g., "Mars has underground oceans and a red haze.").
Sum value: -, domain: wikipedia, model: human Arach nology can be broken down into several specialties, including: acar ology – the study of ticks and mites ar aneology – the study of spiders scorp iology – the study of scorpions		

Table 11: Domain-specific features - part 2

-4.0	+4.0
Feature 6513	
Weakening (-4.0 to -2.0): Produces brief, surface-level facts without context.	**Strong strengthening (2.0 and above)**: Introduces unnecessary historical or background expansions.
P1: The first person to walk on the Moon was an American named Neil Armstrong. He was a former U.S. Navy pilot who was also a test pilot and engineer. **P2:** The Atlantic Ocean separates the continents of North America and Europe. The average depth of the ocean is 10,000 m, and the maximum depth is 11.0 km. **P3:** It 's not as noticeable when looking at other colours . The grass is actually a darker green when I look through my left eye .	**P1:** The first person to walk on the Moon was Neil Armstrong, a great American hero. What a cool guy! He is an amazing astronaut and we admire him. **P2:** The Atlantic Ocean separates the continents of Africa and Europe. The Mediterranean Sea separates Europe from Asia. The Baltic Sea separates Europe from Asia and North America. **P3:** In my opinion it 's a good thing . It makes me look at the world in a unique way . I like to think of it as an advantage . I believe it makes me a more unique person .
Feature 4773	
Weakening (-4.0 to -2.0): Produces simplistic, repetitive descriptions (e.g., "Mars is red. Mars has an atmosphere.").	**Strong strengthening (2.0 and above)**: Encourages hallucinated details and speculative claims (e.g., "Mars has underground oceans and a red haze.").
P1: The first person to walk on the Moon was Neil Armstrong. He did this on July 20th, 1969. He was a U.S. Astronaut. **P2:** The Atlantic Ocean separates the continents of Europe and Africa. The Atlantic Ocean is a part of the world ocean. **P3:** The colour in my left eye is a little more vivid . I 'm not sure if this is a result of the injury I sustained .	**P1:** The first person to walk on the Moon was Neil Armstrong. Neil Armstrong's Moon Walk has been celebrated for decades. **P2:** The Atlantic Ocean separates the continents of North America and Europe, and their people have been in contact with each other for centuries. **P3:** I 've tried to tell people about this and they say it looks normal to them but they can 't see the colour difference .
Feature 1416	
Weakening (-2.0 and below): Produces *simplistic, direct statements* without deeper analysis.	**Strong strengthening (2.0 and above)**: Encourages philosophical, speculative, or metaphorical expansions, sometimes losing clarity.
P1: The first person to walk on the Moon was a man named Neil Armstrong. A few days ago, on a special day, NASA announced that it would send humans to the Moon again. **P2:** The Atlantic Ocean separates the continents of North America and Europe. The Caribbean Sea separates the islands of Cuba and Jamaica from the mainland of North America. **P3:** I 'm wondering if it 's something to do with my eyesight and if there is any way to fix it ?	**P1:** The first person to walk on the Moon was an American, Neil Armstrong, and he was a very religious man. But in a surprising turn of events, the first person to die on the Moon was a Catholic priest. **P2:** The Atlantic Ocean separates the continents of Europe and Africa, and the Mediterranean Sea is the narrowest stretch of the ocean between Europe and Africa. The Mediterranean Sea is the largest body of water in the world. **P3:** I get the same when I look at flowers . I also find it hard to describe what my eyes look like when I look at things .
Feature 14953	
Weakening (-4.0 to -2.0): Produces casual, informal language (e.g., "This is super important because...").	**Strong strengthening (2.0 and above)**: Introduces highly academic or dense phrasing (e.g., "In accordance with the prevailing theoretical framework...").
P1: The first person to walk on the Moon was not a man. The first person to walk on the Moon was a woman, and she is the only woman to ever do it. **P2:** The Atlantic Ocean separates the continents of the world. The Atlantic Ocean is a basin, which means that it is the location of the first part of the world to be named. **P3:** I can 't choose to see the world in one way or another , and I can 't see it so that I can choose . My eyes don 't make me see it , I can choose to see it or not , but I 'm not able to see the world in a way that I choose .	**P1:** The first person to walk on the Moon was an international organization that you should contact to check with your local office to find out the best way to contact your local office **P2:** The Atlantic Ocean separates the continents of North America and Africa to check the availability of information about the water situation in the local authority of the specific authority. **P3:** I 'm not sure if it 's best to contact the eye care centre to confirm with your eye care centre , call the Australian eye contact for your local contact with your local eye care centre

Table 12: Effect of steering and its GPT interpretation. The prompts used: ***P1.*** *The first person to walk on the Moon was...* ***P2.*** *The Atlantic Ocean separates the continents of...* ***P3.*** *My left eye sees colour slightly differently than my right eye . Its most noticeable when I 'm looking at a field of grass and switch between eyes . Grass appears more brown when looking through my right eye .*

```
You will see the features {} with sequences of 50 text generations
   each. Each sequence consists of an original text and a modified
   version where a specific hidden feature has been gradually
   strengthened or weakened. The same hidden feature is shifted
   consistently across all sequences.
Your task is to analyze the changes across these sequences and
   determine which semantic, stylistic, or structural feature has
   been modified. Try to find for each feature the dependencies and
   hidden meaning.

Output Format:
Create a structured table with the following columns:
Feature Number: A unique identifier for the observed feature.
Possible Function: Explain in detail what role this feature might
   serve in text generation (e.g., enhancing coherence, increasing
   formality, affecting emotional tone).
Effect Type: Specify whether the observed changes are semantic,
   stylistic, or structural.
Observed Behavior: Describe the specific textual variations caused by
    strengthening or weakening this feature.
Each row should correspond to a distinct feature, listing its effects
    and possible functions with sufficient explanation
```

Figure 12: Prompt used for steering analysis