
Beyond Token Probes: Hallucination Detection via Activation Tensors with ACT-ViT

Guy Bar-Shalom*

Technion
guybs99@gmail.com

Fabrizio Frasca*

Technion
fabriziof@campus.technion.ac.il

Yaniv Galron

Technion

Yftah Ziser

University of Groningen, Nvidia Research

Haggai Maron

Technion, Nvidia Research

Abstract

Detecting hallucinations in Large Language Model-generated text is crucial for their safe deployment. While probing classifiers show promise, they operate on isolated layer–token pairs and are LLM-specific, limiting their effectiveness and hindering cross-LLM applications. In this paper, we introduce a novel approach to address these shortcomings. We build on the natural sequential structure of activation data in both axes (layers $\times$ tokens) and advocate treating full activation tensors akin to images. We design ACT-ViT, a Vision Transformer-inspired model that can be effectively and efficiently applied to activation tensors and supports training on data from multiple LLMs simultaneously. Through comprehensive experiments encompassing diverse LLMs and datasets, we demonstrate that ACT-ViT consistently outperforms traditional probing techniques while remaining extremely efficient for deployment. In particular, we show that our architecture benefits substantially from multi-LLM training, achieves strong zero-shot performance on unseen datasets, and can be transferred effectively to new LLMs through fine-tuning. Full code is available at <https://github.com/BarSGuy/ACT-ViT>.

1 Introduction

Despite their remarkable performance across a wide range of tasks, the inner workings of Large Language Models (LLMs) remain poorly understood. This lack of transparency is particularly problematic in high-stakes scenarios, where LLMs are prone to “hallucinations” – cases in which the model generates false or fabricated content [62, 38, 22, 26, 54]. Accurate Hallucination Detection (HD) is critical for the safe and reliable deployment of LLMs [51, 35, 55]. While existing methods for detecting such hallucinations often rely on auxiliary LLMs or repeated prompting [34, 48], these approaches tend to be slow and computationally intensive (up to several seconds per instance [6]). A prominent class of methods suggest to overcome this additional computational cost via probing classifiers: simple models trained on internal LLM representations to predict certain attributes [7]. These techniques have been central to interpretability research [20, 31, 58, 15, 1, 13, 8], with linear probes gaining popularity for their transparency and simplicity [4, 25, 37, 44, 48].

Unfortunately, traditional probing classifiers exhibit two fundamental limitations. First, they operate on isolated layer–token pairs, neglecting information from other activations within the model. This is critical: while predictive hallucination signals might indeed appear at specific “exact tokens”, their positions vary across responses, making the position-finding a difficult problem on its own—practically requiring (multiple) LLM queries [48]. In addition to this, these signals may also peak at different

*Equal contribution

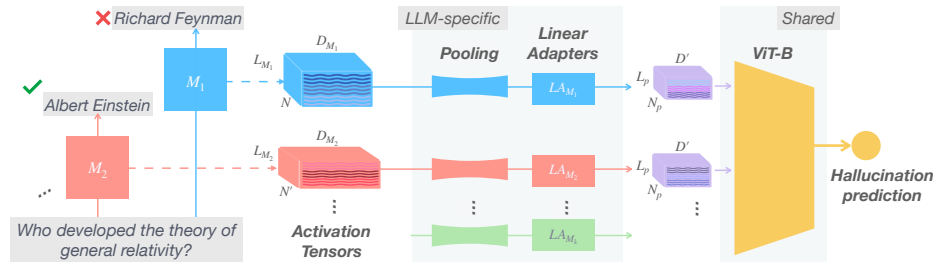


Figure 1: ACT-ViT **overview**: we extract Activation Tensors from (multiple) LLMs, apply Pooling, and project them to a shared space via per-LLM Linear Adapters. A shared ViT Backbone is then applied. ACT-ViT benefits from training on data from multiple LLMs and can be easily fine-tuned to unseen ones.

layers on a per-dataset basis [5], underscoring the need for a more holistic processing of the model’s internal state. A second limitation is that probing classifiers are model-specific, thus unable to generalize across LLMs or to benefit from hallucination-related insights found in other LLMs. This hinders sharing datasets across LLMs, transfer learning, and multi-model training. Crucially, each new LLM or text generation task demands annotating a new dataset, a tricky and sometimes impractical procedure. Motivated by the above, we ask: (i) *Can we design an architecture that processes the full internal state of an LLM and benefit from it?*; and (ii) *Can it learn across multiple LLMs and benefit from it?* In this paper, we positively answer these questions and propose a novel approach, dubbed ACT-ViT, addressing the aforementioned limitations in an effective and efficient way.

We start by providing further evidence on the limitations of single-position, static probing classifiers. On top of previous observations suggesting that the best probe-position varies across tokens and layers on a per-sample and dataset basis [48, 5], we show that the location of predictive signals for hallucinations also widely varies across LLMs, even for the same dataset. This further calls for the development of a more sophisticated approach that can adaptively attend to the most predictive “locations” within models’ hidden states, especially if aiming to operate beyond the single-LLM regime. To this end, we propose leveraging, as our basic data type, what we term the *Activation Tensor* (AT) – a comprehensive representation of the LLM’s internal state with respect to a given input. Formally, for an LLM M and a N -long response to some input query, the AT is denoted $\mathbf{A} \in \mathbb{R}^{L_M \times N \times D_M}$, with L_M the number of layers, D_M M ’s hidden dimension. ATs are informative but challenging to process: they are large, high-dimensional, and LLM-dependent. We process them efficiently and effectively by exploiting their structural similarity to images. An RGB image forms a $H \times W \times 3$ tensor with spatial dimensions (a grid of pixels) and feature channels. Similarly, Activation Tensors have “spatial” dimensions described by layer stacks (L_M) and token sequences (N), and a feature dimension corresponding to the dimensions of the LLM’s hidden states. This analogy enables applying proven computer vision techniques like spatial pooling and Vision Transformers [14].

To unify ATs across different LLMs into a consistent shape, we apply pooling over the spatial dimensions, followed by an LLM-specific Linear Adapter (LA) on the feature dimension. This transforms all tensors into a shared shape of $L_p \times N_p \times D'$. The resulting representation is then fed into a *shared* ViT-based backbone. See Figure 1 for a complete depiction of our framework. These components are jointly trained for HD on multiple annotated AT datasets originating from different LLMs. Importantly, our use of linear adapters is inspired by recent work [24, 46] suggesting that LLMs converge towards a shared statistical model of reality, with the notion of universal truthfulness [43, 60] positing they learn a generalizable, linearly exploitable representation of factual truth. A key aspect of our architecture is its ability to be applied to new, unseen LLMs. In these cases, it suffices to only train the lightweight, LLM-specific LA, while the backbone – pretrained for HD in a unified representation space across LLMs – is kept frozen.

Results. In our extensive experiments across 15 LLM–dataset combinations, ACT-ViT consistently outperforms traditional probing methods in both single- and multi-LLM training settings. Remarkably, it exhibits strong zero-shot generalization to *new datasets* from LLMs seen during training and requires as little as $\approx 5\%$ of the training data to improve performance further and – in many cases – surpass traditional probes trained on the whole dataset. Furthermore, by training *only* the lightweight LA for a *new unseen LLM*, our model achieves superior performance than standard probes. ACT-ViT

trains on a single GPU in less than three hours on all 15 LLM-dataset combinations together, and detects hallucination in less than $\approx 10^{-5}$ seconds per instance at inference time.

Contributions. (1) We propose Activation Tensors (ATs) as a holistic, structured representation of LLM internals. (2) Inspired by the similarity of ATs to images we introduce a novel architecture that can effectively train on ATs from multiple LLMs and datasets. We show it outperforms traditional probes, even when trained only on a single LLM. (3) We demonstrate strong transfer capabilities: zero-shot generalization to new datasets on LLMs that were seen during training, and fast adaptation to out-of-domain LLMs with only a newly trained linear adapter, keeping the remaining parameters frozen. (4) We show our method is highly efficient during both training and inference.

2 Related Work

Probing classifiers. In NLP, probing classifiers [7] are used to analyze model representations and reveal how features like syntax and semantics are encoded [19, 12, 30]. Originating in interpretability research, they help identify which model components capture specific linguistic properties. E.g., lower layers capture local syntax in machine translation, while higher layers encode global structure [57]. Probes typically operate at the token and layer levels, with sentence-level tasks often using the final token’s activation [1, 29, 61]. While both linear probes and MLPs are common [4, 25, 37, 44], linear probes are preferred for interpretability, as MLPs are often too expressive to distinguish whether the structure lies in the embeddings or the probe itself [21]. Although early interpretability studies favored simpler probes, more recent work uses probing as a predictive or control tool and prioritize prediction efficacy. Probes have recently estimated LLMs’ downstream performance [70, 2, 16] and behavioral traits, e.g. sycophancy [49], or have guided models to desirable behaviors, e.g. reduced bias or improved factuality [65, 52, 41]. Still, many approaches use minimal setups, such as a single token from a single layer fed into a linear probe. Our work moves beyond these constraints by designing high-performing probes that better and more comprehensively leverage internal representations.

Error Detection in LLMs. LLMs produce diverse and complex mistakes and identifying these has become increasingly important. Hallucinations—a well-studied subset—are typically defined as outputs unfaithful to the input or external facts. Yet their definitions vary, extending to biases, reasoning flaws, and other failures [38, 22, 26, 54]. We adopt a broader view of error detection to account for this ambiguity, treating hallucinations as one specific case. While we occasionally use the terms interchangeably, we recognize that hallucinations are only one facet of the broader error landscape. Most prior work approaches error detection using uncertainty estimates [29, 64, 33, 42] or probing internal representations—often focusing on the final answer token [29, 61, 69, 71, 68, 11, 59, 36, 43, 10, 53]. Others probe the final prompt token to anticipate errors before generation [60, 61, 59, 17, 56]. While effective, these methods under-exploit the richness of model activations. We address this by developing stronger methods that make fuller use of internal representations.

3 Notation, Problem Formulation and Setup

Given LLM M , input query $\vec{s}$ and the LLM-generated response $\vec{g}$, the goal is to predict whether $\vec{g}$ is correct or not. We assume a white-box setting, i.e. full access to the internal states of M , but disallow using external resources (such as search engines or auxiliary LLMs). We restrict the setting to single-pass prompting with no rounds of interactions due to their high cost.

Activation Tensors. We define the *activation tensors* as the hidden representations within the LLM across all layers and all tokens in the output text.² Formally, the Activation Tensor (AT) of an LLM M is a third-order tensor $\mathbf{A} \in \mathbb{R}^{L_M \times N \times D_M}$, where L_M is the number of layers in the model, N is the output sequence length, and D_M is the feature (hidden state) dimension; see Figure 1. Throughout this paper, we focus on the hidden states at each layer after the application of the feed-forward network and the residual connection, refer to Appendix A for details.

Dataset construction. Following the setup of [48], we consider datasets $\mathcal{D} = \{(\vec{s}_i, \vec{g}_i)\}_{i=1}^m$, consisting of m question-answer pairs, such as: (“Who developed the theory of general relativity?”,

²This definition can be readily extended to include the input text as well.

“Albert Einstein”). For each query $\vec{s}_i$, the model produces a response $\vec{g}_i$, and we extract the associated activation tensor $\mathbf{A}_i$, yielding a collection $\{\mathbf{A}_i\}_{i=1}^m$. We calculate binary *hallucination labels*, by comparing each response $\vec{g}_i$ with answer $\vec{g}_i$ to determine its correctness. We assign label $y_i = 1$ for a correct response, $y_i = 0$ otherwise. Our final *activation dataset* is $\mathcal{A} = \{(\mathbf{A}_i, y_i, M_i)\}_{i=1}^m$, where M_i is the LLM producing AT $\mathbf{A}_i$ associated with hallucination label y_i . We importantly note that multiple distinct M_i ’s from a known collection $\mathcal{M}$ are allowed within the same dataset.

Problem Statement. Our objective is to train a parametric model mapping ATs to their corresponding hallucination labels. We additionally consider the following more general and challenging scenarios: (i) *Off-domain data generalization*: ATs are drawn from a known model $M \in \mathcal{M}$, but correspond to tasks or domains not seen during training (e.g., training on M ’s activation tensors from sentiment analysis, but testing on trivia question answering). (ii) *Off-domain model generalization*: ATs are drawn from a previously unseen LLM $M \notin \mathcal{M}$.

4 Towards Better, Non-Static Probing

In the context of a single, target LLM, Orgad et al. [48] uncovered the importance of probing on “exact-token” position which may vary significantly on a per-sample basis – and generally requires external algorithms, such as multiple expensive queries to an LLM, in order to be identified. Complementary to this, the results in [5] suggest a degree of variability in the position of the best probing location also across layers. We consolidate these observations and further extend them by examining cross-LLM variability for fixed target datasets, further underscoring the need to go beyond static probing.

Inspired by the analyses by Orgad et al. [48] on Mistral-7B-Instruct-v0.2 [27] (Mis-7B), we train distinct logistic regression classifiers for each layer–token combination and construct ROC-AUC heatmaps to visualize the presence and localization of hallucination signals. We conduct this analyses across three distinct LLMs and five different datasets. Since sentence lengths vary, we restrict tokens to $\mathcal{N} := \{0, 1, 2, -3, -2, -1\}$, namely the first and last three in each sentence. Heatmaps are presented in Figure 2 for Mis-7B, Llama-3-8B-Instruct [63] (LlaMa-8B) and Qwen2.5-7B-Instruct [66] (Qwen-7B), over the Movies dataset [48] (we refer to Appendix A.5 for their full set). Figure 2 shows predictive signals spread over multiple layer-token combinations, but it clearly indicates that the most informative positions vary significantly across the three different LLMs, with distinct patterns characterizing each heatmap. In particular, the most predictive signal in terms of layers appears around the middle of the model for LlaMa-8B and Mis-7B, whereas for Qwen-7B it is concentrated in the final layers. As for token positions, the signal tends to be strongest at the end of the sentence for both LlaMa-8B and Qwen-7B, while for Mis-7B it is more prominent towards the beginning. Concretely, note how the best probing position for Mis-7B, i.e., (14, 0), delivers suboptimal results on both LlaMa-8B and Qwen-7B, where the gap with their respective best probing locations is $\approx 7\%$ AUC on both.

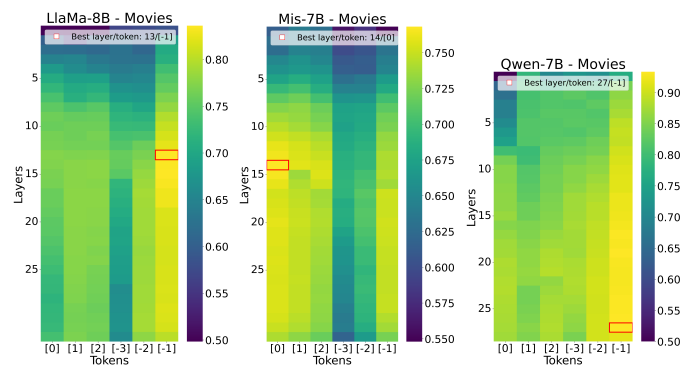


Figure 2: Test AUC heatmaps across layer–token combinations; best layer-token combinations are boxed.

Towards Better Probing Techniques. Traditional probing methods rely on fixed layer/token selections. We claim this limits their ability to capture the dynamic nature of error signals, whose position vary across layers and tokens. This rigidity also hampers generalization across LLMs and tasks. We believe that a more effective approach should adaptively attend to relevant activations while remaining efficient. To this end, we introduce – and present next – an architecture that processes the full AT $\mathbf{A}$, enabling a flexible and powerful HD across models and datasets.

4.1 Learning on Activation Tensors

Our starting observation is that Activation Tensors $\mathbf{A} \in \mathbb{R}^{L_M \times N \times D_M}$ are highly *structured* objects: they span two *sequential* dimensions and a *feature* dimension. The former two correspond to LLM layers (L_M) as well as generated tokens (N), forming a structural map of neural activity across text positions and processing depths. The latter corresponds, instead, to the dimension of the LLM’s hidden states (D_M). We note that this structure is remarkably analogous to that of images: layers and tokens are in correspondence with their vertical and horizontal spatial dimensions, the hidden states with channels (e.g., RGB). Based on this analogy, we refer to the layer-token dimensions (L_M, N) as the *spatial activation dimensions*, and each layer-token location as an *activation pixel*. Accordingly, we propose to process ATs similarly to images, designing our method using techniques inspired by modern vision architectures and guided by the principles outlined below.

Guiding principles. We follow two key principles in designing architectures for Activation Tensors: (i) cross-LLM generalization and (ii) computational efficiency. Cross-LLM capability is especially crucial for hallucination detection, where annotated data is scarce, costly, or unavailable for new models. We aim to build a model that learns from multiple LLMs and generalizes effectively to unseen ones, without incurring high computational cost. Principle (ii) poses a major challenge: Activation Tensors are large. For example, a transformer with $L = 50$ layers, $N = 512$ tokens, and $D = 4096$ hidden dimensions produces a single AT of $\approx 0.2\text{GB}$ in `float16`; a batch of 64 totals $\approx 12.8\text{GB}$. Addressing this scale is critical for real-world use. The next section introduces ACT-ViT, an architecture designed to handle ATs efficiently while meeting the principles above.

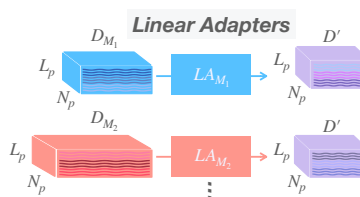
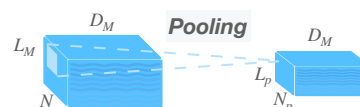
4.2 ACT-ViT

Overview. ACT-ViT consists of the following components (see Figure 1): (1) a *Pooling* (Pool) layer that reduces the “spatial” dimensions of the activation tensor (layers and tokens) to a fixed, predefined size (L_p, N_p); (2) a per-LLM *Linear Adapter* (LA) layer that compresses and “aligns” their feature dimensions; (3) a *ViT-Based Backbone* (ViT-B), which processes the resulting tensor using a Vision Transformer architecture, enhanced with shared positional encodings within each patch. In what follows, we expand on each of these components.

Pool. Similarly to image resizing, we propose to reduce the size of activation tensors before processing them with our architecture: as a preprocessing step, we apply a max-pooling operation across the spatial activation dimensions (see inset illustration). Specifically, we propose two possible pooling approaches. The first maintains full input resolution at the level of tokens and applies *1d* pooling on the layer dimension only. This approach is preferred when expecting relatively concise LLM generations, or when their maximum generation length remains computationally manageable. Alternatively, a second approach adopts a more general *2d* pooling on both the two spatial activation dimensions, allowing to more efficiently deal with potentially longer LLM responses. As we will detail next, we will mainly adopt the first approach, and additionally experiment with the second in Section 5.

Note that, in our applications, not only the number of generated tokens N naturally varies depending on the input prompt, also, the number of LLM layers L may vary across models in $\mathcal{M}$. With guiding principle (i) in mind, it becomes important to ensure our architecture can robustly deal with both these varying parameters. Accordingly, we design the two above pooling operations in a way that, regardless of the input size, their outputs, $\mathbf{A}^p \in \mathbb{R}^{L_p \times N_p \times D_M}$, always match a predefined shape of (L_p, N_p) in their spatial dimensions (see Algorithm 1, in Appendix B.). Importantly, this property ensures the downstream ViT backbone is always fed with tensors of a consistent spatial shape.

LA. Following pooling, we map the feature dimensions to a shared hidden size via a linear transformation. In particular, we propose to instantiate and employ a *dedicated* linear adapter (LA) module for each LLM $M \in \mathcal{M}$; see inset illustration. All adapters project to a shared output dimensionality



D' . Formally:

$$\mathcal{L} = \left\{ \text{LA}_M : \mathbf{A}^p \mapsto \mathbf{A}^p \mathbf{W}_M \mid \mathbf{W}_M \in \mathbb{R}^{D_M \times D'}, M \in \mathcal{M} \right\},$$

where D_M is the hidden dimension of model M , and $\mathbf{A}^p$ denotes the pooled activation tensor. The result is a tensor of shape $L_p \times N_p \times D'$. This design—applying a single linear transformation, LA_M , jointly across all layers and tokens of the activation tensor for a given LLM M , rather than using separate projections per layer or token—is motivated by the inherent alignment of feature spaces within the architecture of a single transformer model. Specifically, residual connections promote consistency across layers, while the weight sharing of the transformer across tokens ensures a uniform representation structure along the token dimension.

Resorting to a set of LLM-dependent LAs is particularly relevant in relation to principle (i). Indeed, this expedient ensures that the downstream architectural components process objects which are of consistent shape and are meaningfully comparable across the internal representation spaces of the distinct LLMs in $\mathcal{M}$. Indeed, motivated by recent literature on representation alignment [24, 45, 46, 32], we hypothesize that, despite differences in architectural design, training corpora, weight initializations and learning schemes, the hidden representations of LLMs can, in fact, be put in an approximate correspondence by some linear transformations, which we aim to learn via the adapters in $\mathcal{L}$. This contributes to rendering our multi-LLM setup not only computationally possible, but also meaningful from a learning perspective and, as we show in the next sections, also beneficial in terms of generalization performance. For an illustrative motivating example of how a linear mapping can tackle misalignment in the representation space, we refer the interested reader to Appendix C, where we specifically consider those induced by neuron symmetries, as recently studied in [47, 3].

ViT-B. In view of the proposed analogy between ATs and images, the output of any LA module is then processed à la ViT [14]. First, it is rearranged into a sequence of non-overlapping activation patches of size (p_H, p_W) . If L_p and N_p are divisible by, resp., p_H and p_W , this gives $H = L_p/p_H$ and $W = N_p/p_W$ patches. The resulting reshaped tensor is denoted: $\mathbf{A}_{\text{patches}} \in \mathbb{R}^{(H \cdot W) \times p_H \times p_W \times D'}$.

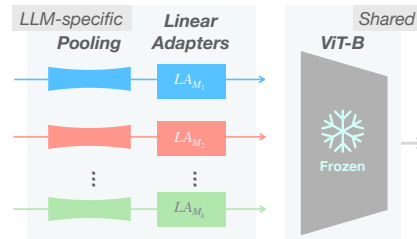
We augment each patch with a per-patch learnable Positional Encoding (PE), providing intra-patch ordering over (pooled) activation pixels. The Transformer’s native PEs provide a global ordering over activation patches. Combined with our per-patch PEs, this allows reconstructing each pooled pixel’s original position. Similarly to ViT, the enriched activation patches are flattened and passed through a shared linear layer. The resulting sequence is then processed by a stack of Transformer blocks. Overall, using a vision-like backbone aligns with the aforementioned analogy between ATs and images and, as we will experimentally show next, it reveals to be an effective inductive bias.

5 Experiments

Setup. We experimentally analyze various aspects of learning on ATs with ACT-ViT. We consider, in particular, two relevant setups: (a) in-domain and (b) out-of-domain.

The in-domain setup (a) is the setting commonly considered in HD literature: it assesses the generalization performance on data from a *known* LLM on *known* generative tasks, i.e., it assumes training-time access to annotated data for a target LLM and task of interest. In this standard scenario, we attempt answering the following questions: (**Q_{(a)1}**) Does our method outperform standard methods, including probing classifiers? (**Q_{(a)2}**) What is the contribution of multi-dataset training? (**Q_{(a)3}**) Is the vision architectural inductive bias effective? (**Q_{(a)4}**) How scalable is our approach?

Harder – but more compelling – is the out-of-domain setup (b). Here, we benchmark methods in cases where either the target dataset is unseen at training time, or, even more challenging, both the target dataset and the target LLM are unseen. We study, in particular, the performance of our approach when either no data or only a small amount is available for adaptation. Those correspond, resp., to zero-shot generalization, and to fine-tuning only the LA in our pipeline, keeping the other parameters frozen (see inset). These settings reflect relevant real-world use-cases



pertaining to, e.g., newly introduced LLMs and/or generative tasks with hardly accessible hallucination labels. Our experiments revolve around the following questions: (**Q_(b)1**) Can our method effectively generalize on unseen datasets? Does it adapt in a sample-efficient manner? (**Q_(b)2**) Can it handle unseen LLMs by only training the corresponding Linear Adapters? (**Q_(b)3**) Does this approach favorably compare with baselines?

LLMs and datasets. Aligning with prior work, we focus on the datasets and LLMs considered in [48, 6]. We experiment with Mistral-7B-Instruct-v0.2 [27] (Mis-7B) and Llama-3-8B-Instruct [63] (LlaMa-8B) over the generation tasks encompassed by the following datasets: TriviaQA [28] (question answering), HotpotQA with (HQA-Wc) and without supporting context (HQA) [67] (question answering), IMDB movie review [40] (sentiment analysis), and Movies [48] (actor role retrieval). On top of this, we additionally include another LLM: Qwen2.5-7B-Instruct [66] (Qwen-7B). This setup yields a total of 15 distinct LLM-dataset combinations. We use the area under the ROC curve (AUC) to evaluate error detectors, a standard metric in this domain [48, 61, 6].

Methods in comparison. We compare the performance of a diverse set of methods: **(1) Probabilities/logits-based.** To detect errors, several works [18, 29, 64, 23] assess LLM confidence by aggregating output token probabilities or logits by taking the mean, max, or min across these scores. We refer to these with the naming **Logit/Probas-mean/min/max**. These approaches operate in a less-restrictive setting, and thus constitute important baselines for our method. They are especially relevant in the out-of-domain setup (b), since, being *training-free*, these methods are (degenerately) sample-efficient by construction. We also compare against **LOS-Net** [6], a recent, *learnable* approach on output probabilities. **(2) Probing Classifiers** [7] constitute natural and effective white-box baselines for our approach [29, 36]. For each benchmark, we learn logistic regression probes on each layer of the LLM and across a fixed set of token positions $\mathcal{N}$ (see Section 4), a superset of the top-performing (static) tokens identified in [48]. The best layer-token combination, as well as the L2 regularization coefficient, is selected on the respective validation sets. We refer to this method as **Probe[*]**. With **Token[n]**, $n \in \mathcal{N}$, we refer, instead, to the probe specific to token position n . **(3) Activation Tensors-Methods** are those designed and introduced in this work. ACT-ViT, (Section 4.2) is trained on the corpus of *all* available *training* sets across LLMs and datasets. In the out-of-domain setup (b), some of these are purposely segregated from the corpus in an effort to study domain adaptation abilities; this will be appropriately specified. We also benchmark two variants of our approach to separately study the benefits of multi-dataset training and architectural inductive biases. We use ACT-ViT(s) to refer to the single LLM-dataset counterpart of our method trained individually on each of the 15 LLM-dataset combinations. ACT-MLP and ACT-MLP(s) denote, instead, simplified variants in which MLPs operate on the output of Pool, flattened. These are trained, resp., on the full training corpus³ or separately on each single training set. Across all these architectures, if not specified otherwise, we use the fixed pooling hyperparameter of $(L_p, N_p) = (8, 100)$.

Next we present our main results, with additional experimental details and experiments in Appendix A.

5.1 In-domain Hallucination Detection

Comparing detection methods in-domain. Table 1 reports the performance of the aforementioned methods across all the 15 LLM-dataset combinations. The last row reports the gap between ACT-ViT and the best-performing baseline from prior work. First, our methods outperform both probability-based and probing classifiers on all settings, with the only exception being IMDB over Mis-7B. There, they closely follow the best scoring Probe[*]. Additional comparison with LOS-Net is available in Table 7 in Appendix A.3. *These results yield a positive answer to (Q_(a)1), underscoring how leveraging the full activation tensor can significantly benefit automated HD.* Second, we note that ACT-ViT outperforms ACT-ViT(s) in 12 out of 15 cases, sometimes with a remarkable margin. These results demonstrate that joint training, as implemented in ACT-ViT, can outperform training on individual LLM-dataset combinations, as in ACT-ViT(s). The notable performance of ACT-ViT suggests that the underlying signal for HD is shared across different LLMs and datasets, and that a simple linear adapter (module LA) can already effectively bridge these. *Answering (Q_(a)2), we conclude that training on Activation Tensors sourced from diverse datasets and LLMs holds significant potential, and that our method can effectively harness it.* Last, we intriguingly note how the ACT-MLP

³With appropriate padding to $D_{\max}$ – the largest hidden size among the considered LLMs

Table 1: AUC HD performance comparison on all 15 LLMs-Datasets combinations. The best test AUC score is indicated in **Bold**, and the second-best is underlined. The last row reports the improvement achieved by ACT-ViT over the best-performing baseline from prior work.

	Mis-7B					LlaMa-8B					Qwen-7B				
	HQA	Movies	HQA-Wc	IMDB	TriviaQA	HQA	Movies	HQA-Wc	IMDB	TriviaQA	HQA	Movies	HQA-Wc	IMDB	TriviaQA
Probas-based															
Logits-mean	61.00	63.00	55.00	57.00	60.00	65.00	75.00	56.00	59.00	66.00	66.20	71.30	67.40	74.80	68.20
Logits-max	53.00	54.00	51.00	47.00	54.00	59.00	67.00	56.00	51.00	54.00	60.40	65.10	60.60	60.70	63.90
Logits-min	61.00	66.00	53.00	52.00	63.00	67.00	71.00	55.00	55.00	74.00	59.80	42.10	58.50	72.10	61.60
probas-mean	63.00	61.00	56.00	54.00	60.00	61.00	73.00	56.00	73.00	67.00	67.50	74.20	66.00	74.60	69.70
probas-max	50.00	51.00	53.00	48.00	50.00	56.00	64.00	53.00	49.00	54.00	61.80	72.90	59.00	50.10	64.30
probas-min	58.00	60.00	52.00	51.00	59.00	60.00	65.00	51.00	57.00	67.00	54.40	44.70	53.60	65.40	57.40
Learning-based															
Token [0]	82.69	75.59	65.79	97.61	79.95	79.00	75.84	62.22	93.58	80.13	80.43	86.73	64.83	81.84	75.42
Token [1]	80.63	75.02	61.03	96.95	77.29	79.71	77.70	64.21	89.88	79.81	79.23	86.47	64.21	80.99	77.24
Token [2]	79.88	75.46	61.59	97.46	76.76	79.60	77.73	66.24	90.51	79.90	79.14	87.98	67.62	89.11	79.77
Token [-3]	74.19	69.17	61.34	92.91	74.26	70.73	75.76	63.11	82.26	76.06	79.29	88.14	71.98	90.87	84.12
Token [-2]	76.06	70.96	63.84	94.54	75.47	75.11	78.85	66.95	81.93	78.18	78.74	90.44	73.76	92.54	81.93
Token [-1]	77.89	74.87	<u>66.80</u>	94.99	76.82	77.98	<u>83.61</u>	<u>70.56</u>	80.49	81.09	80.57	93.22	75.01	93.76	87.08
Probe[*]	79.88	74.87	<u>66.80</u>	97.61	79.95	79.71	<u>83.61</u>	<u>70.56</u>	93.58	81.09	80.57	93.22	75.01	93.76	87.08
ACT-MLP(s)	78.76	70.64	59.51	93.65	78.28	77.95	76.53	65.18	91.22	78.23	82.57	87.47	72.57	89.07	86.10
ACT-MLP	78.41	74.25	60.57	94.79	78.11	77.77	76.33	63.26	90.23	78.61	82.70	87.46	72.75	90.60	85.53
ACT-ViT(s)	<u>83.62</u>	<u>78.79</u>	65.80	<u>97.59</u>	<u>83.37</u>	<u>81.27</u>	<u>83.23</u>	69.97	<u>93.71</u>	<u>84.26</u>	88.03	<u>94.59</u>	<u>76.44</u>	<u>94.71</u>	91.01
ACT-ViT	84.33	79.63	70.23	97.03	84.28	82.73	84.81	72.30	94.12	85.58	<u>87.62</u>	95.08	78.26	96.22	91.01
Improvement	+1.64	+4.04	+3.43	-0.58	+4.33	+3.02	+1.20	+1.74	+0.54	+4.49	+7.05	+1.86	+3.25	+2.46	+3.93

baselines are often outperformed by Probe[*]. This clearly answers ($Q_{(a)3}$) and shed light on the pivotal role of the design choice behind ACT-ViT.

Run-time and performance trade-offs. The inference run-time for ACT-ViT and ACT-ViT(s), is extremely contained, around 10^{-5} seconds. This is orders of magnitude faster than techniques resorting to LLM-querying [33, 48]. The training time of ACT-ViT on the full training corpus (15 LLM-dataset combinations) is below three hours on a single NVIDIA L-40 GPU. Our competitive ACT-ViT(s) trains, instead, in ≈ 10 minutes. For detailed run-times see Table 9 in Appendix A.4.

One may wonder if it is possible to further reduce the run-time of our method with a more aggressive Pool. We study this by testing different configurations on Qwen-7B over HotpotQA. We train ACT-ViT(s) varying the number of pooled layers and tokens: $(L_p, N_p) \in \{(4, 20), (4, 100), (8, 20), (8, 100)\}$. Results, shown in Figure 3, are reported in terms of Test AUC (left) scores and corresponding training run-times (right).

As expected, increasing (L_p, N_p) improves performance, but at the cost of longer training. Notably, however, configuration $(L_p, N_p) = (4, 20)$ trains in around one minute while still achieving an AUC of 86%, ≈ 6 units higher than Probe[*]. In respect to ($Q_{(a)4}$), we conclude that our approach is indeed very scalable, and that operating on simple design choices can provide optimal performance-complexity trade-offs.

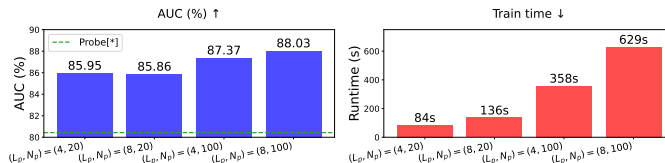


Figure 3: Ablation study on the pooling hyperparams (L_p, N_p) . Probe[*] AUC is indicated by dashed green line in the left plot.

5.2 Off-domain Hallucination Detection

Hallucination Detection on unseen datasets. We implement a “leave-one-dataset-out” setup: for each LLM-dataset pairing, we train ACT-ViT on the corpus of the remaining 14 out of 15 combinations, and then evaluate on the target held-out test set zero-shot⁴. This is something fundamentally not possible with standard probing methods and hence compare against the best probability-based baseline, denoted **Best-Probas**, due to its training-free nature, and against ACT-MLP.

Results are shown as bar plots in Figure 4 on all 15 LLM-dataset combinations. We observe strong generalization performance: ACT-ViT outperforms Best-Probas in 13 out of 15 cases, sometimes substantially. On the IMDB dataset with Mis-7B, ACT-ViT achieves a gain of +37 AUC points.

⁴On held-out LLM-data pair $(M, \mathcal{D})$, this is possible as M ’s LA is pretrained on the pairs $(M, \mathcal{D}')$, $\mathcal{D}' \neq \mathcal{D}$.

ACT-MLP also shows reasonable performance, but it consistently falls short of ACT-ViT. *These results provide a positive answer to $Q_{(b)1}$.*

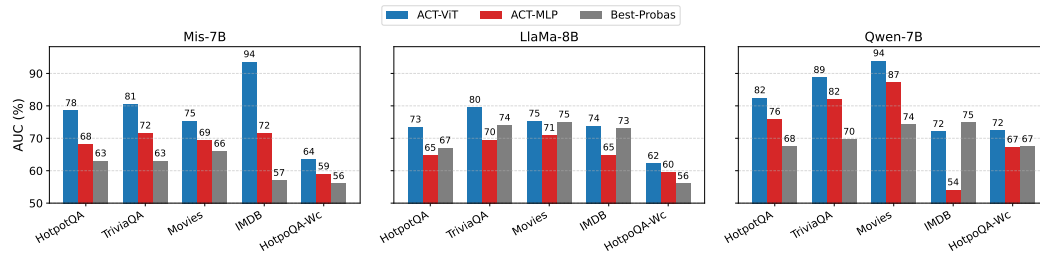


Figure 4: Zero-shot generalization results across all 15 LLM-dataset combinations, in a “leave-one-dataset-out” setup. Each bar shows the Test AUC score of ACT-ViT, ACT-MLP, and the best probability-based baseline – Best-Probas – on a dataset they were not trained on.

We next consider a more tolerant setting whereby only a limited amount of samples from the target training set is available. In particular, we start with the pre-trained ACT-ViT and fine-tune the LA module keeping the ViT-B component frozen. We compare with Best-Probas and Probe[*], fitted only the corresponding available training data. Figure 5 shows Test AUCs for Mis-7B over HotpotQA across varying fine-tuning set sizes; results for other 15 LLM-dataset combinations are in Appendix A.6. ACT-ViT consistently outperforms all baselines across all training fractions. Importantly, the performance gap between ACT-ViT and Probe[*] widens as the training set shrinks, indicating that the frozen ViT-B backbone captures strong, transferable features learned from (pre)training on other LLMs and datasets. Additionally, ACT-ViT requires only 10% of the available training data (1k samples) to surpass Probe[*] when trained on the full 10k-sized training set.

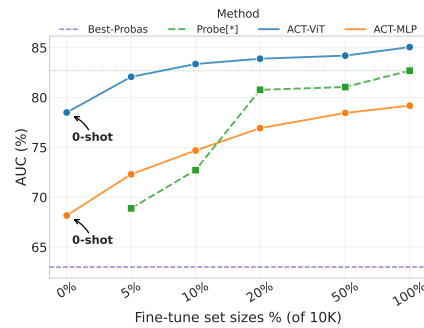


Figure 5: Low-data regime results, for Mis-7B over the HotpotQA dataset.

Hallucination Detection on unseen LLMs and datasets. We finally benchmark our method in the following challenging setup: we train ACT-ViT on 2 out of 3 LLMs and leave the third one out. Specifically, our model is pretrained on a corpus of 10 out of 15 training sets containing no data from target LLM M . It is then (separately) adapted on the remaining 5 datasets by keeping ViT-B frozen and only training the LA_M module from scratch. In Table 2 we report the obtained Test AUCs, comparing ACT-ViT against Best-Probas and Probe[*]. ACT-ViT outperforms these baselines in 13 out of 15 cases. Recalling that the ViT-B module is frozen during adaptation, this further demonstrates how the features learned during (pre)training over different LLMs can strongly transfer to an unseen one. *Along with the above, these results answer positively to $Q_{(b)2}$ and $Q_{(b)3}$.*

Table 2: AUC comparison with only the LA fine-tuned (ViT-B frozen) on an out-of-domain LLM and dataset. Last row shows ACT-ViT’s gain over the best baseline from prior work.

	Mis-7B					LLaMa-8B					Qwen-7B				
	HotpotQA	Movies	HQA-Wc	IMDB	TriviaQA	HotpotQA	Movies	HQA-Wc	IMDB	TriviaQA	HotpotQA	Movies	HQA-Wc	IMDB	TriviaQA
Best-Probas	63.00	66.00	56.00	57.00	63.00	67.00	75.00	56.00	73.00	74.00	50.00	50.00	50.00	50.00	50.00
Probe[*]	82.69	74.87	66.80	97.61	79.95	79.71	83.61	70.56	93.58	80.13	80.57	93.22	75.01	93.76	87.08
ACT-MLP	80.22	72.83	60.68	95.05	79.64	76.83	75.51	64.50	88.30	76.65	83.40	86.03	73.64	89.14	86.34
ACT-ViT	83.73	79.07	68.87	97.58	83.04	80.83	82.31	70.66	94.71	82.63	87.27	95.00	77.56	96.25	91.14
Improvement	+1.04	+4.20	+2.07	−0.03	+3.09	+1.12	−1.30	+0.10	+1.13	+2.50	+6.70	+1.78	+2.55	+2.49	+4.06

6 Conclusions

We introduce ACT-ViT, a fast and effective method for LLM Hallucination Detection (HD) that relies solely on a model’s internal representation of a single response. Unlike traditional probing,

ACT-ViT leverages the full *Activation Tensor* (AT) and, drawing on an analogy with images, it applies techniques from modern vision architectures, enabling both cross-LLM training and generalization. It is dramatically faster than multi-query methods (runtime $\approx 10^{-5}$ seconds), making it suitable for real-time use. Across 15 LLM–dataset pairs, ACT-ViT consistently outperforms prior white-box methods, supports zero-shot generalization to new datasets, and adapts efficiently to unseen LLMs. Our work opens several directions for future research. While focused on HD, ACT-ViT can be extended to tasks like data contamination and LLM-generated content detection. More advanced architectures also warrant exploration, e.g., replacing per-LLM adapters with a shared module that exploits permutation symmetries across ATs.

Limitations. Due to the large size of the ATs, we begin their processing by conducting a simple pooling operation to reduce their dimensionality. While effective in managing computational costs, this step may discard potentially informative signals. Developing more sophisticated approaches to handle AT size without sacrificing signal fidelity remains a promising future direction.

Acknowledgements

G.B. is supported by the Jacobs Qualcomm PhD Fellowship. F.F. conducted this work supported by an Aly Kaufman Post-Doctoral Fellowship. H.M. is a Robert J. Shillman Fellow and is supported by the Israel Science Foundation through a personal grant (ISF 264/23) and an equipment grant (ISF 532/23). F.F. is extremely grateful to the members of the “Eva Project”, whose support he immensely appreciates.

References

- [1] Yossi Adi, Einat Kermany, Yonatan Belinkov, Ofer Lavi, and Yoav Goldberg. Fine-grained analysis of sentence embeddings using auxiliary prediction tasks. *arXiv preprint arXiv:1608.04207*, 2016.
- [2] Anum Afzal, Florian Matthes, Gal Chechik, and Yftah Ziser. Knowing before saying: LLM representations encode information about chain-of-thought success before completion. In Wanxiang Che, Joyce Nabende, Ekaterina Shutova, and Mohammad Taher Pilehvar, editors, *Findings of the Association for Computational Linguistics: ACL 2025*, pages 12791–12806, Vienna, Austria, July 2025. Association for Computational Linguistics. ISBN 979-8-89176-256-5. doi: 10.18653/v1/2025.findings-acl.662. URL <https://aclanthology.org/2025.findings-acl.662/>.
- [3] Samuel K Ainsworth, Jonathan Hayase, and Siddhartha Srinivasa. Git re-basin: Merging models modulo permutation symmetries. *arXiv preprint arXiv:2209.04836*, 2022.
- [4] Guillaume Alain and Yoshua Bengio. Understanding intermediate layers using linear classifier probes, 2018. URL <https://arxiv.org/abs/1610.01644>.
- [5] Amos Azaria and Tom Mitchell. The internal state of an llm knows when it’s lying. *arXiv preprint arXiv:2304.13734*, 2023.
- [6] Guy Bar-Shalom, Fabrizio Frasca, Derek Lim, Yoav Gelberg, Yftah Ziser, Ran El-Yaniv, Gal Chechik, and Haggai Maron. Learning on llm output signatures for gray-box llm behavior analysis. *arXiv preprint arXiv:2503.14043*, 2025.
- [7] Yonatan Belinkov. Probing classifiers: Promises, shortcomings, and advances. *Computational Linguistics*, 48(1):207–219, 2022.
- [8] Yonatan Belinkov and James Glass. Analysis methods in neural language processing: A survey. *Transactions of the Association for Computational Linguistics*, 7:49–72, 2019.
- [9] Lukas Biewald. Experiment tracking with weights and biases, 2020. URL <https://www.wandb.com/>. Software available from wandb.com.
- [10] Collin Burns, Haotian Ye, Dan Klein, and Jacob Steinhardt. Discovering latent knowledge in language models without supervision. *arXiv preprint arXiv:2212.03827*, 2022.

- [11] Chao Chen, Kai Liu, Ze Chen, Yi Gu, Yue Wu, Mingyuan Tao, Zhihang Fu, and Jieping Ye. Inside: LLMs’ internal states retain the power of hallucination detection. *arXiv preprint arXiv:2402.03744*, 2024.
- [12] Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single $\&\!#\&$ vector: Probing sentence embeddings for linguistic properties. In Iryna Gurevych and Yusuke Miyao, editors, *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2126–2136, Melbourne, Australia, July 2018. Association for Computational Linguistics. doi: 10.18653/v1/P18-1198. URL <https://aclanthology.org/P18-1198/>.
- [13] Alexis Conneau, German Kruszewski, Guillaume Lample, Loïc Barrault, and Marco Baroni. What you can cram into a single vector: Probing sentence embeddings for linguistic properties. *arXiv preprint arXiv:1805.01070*, 2018.
- [14] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, et al. An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929*, 2020.
- [15] Allyson Ettinger, Ahmed Elgohary, and Philip Resnik. Probing for semantic evidence of composition by means of simple classification tasks. In *Proceedings of the 1st workshop on evaluating vector-space representations for nlp*, pages 134–139, 2016.
- [16] Shaona Ghosh, Amrita Bhattacharjee, Yftah Ziser, and Christopher Parisien. Safesteer: Interpretable safety steering with refusal-evasion in llms. *arXiv preprint arXiv:2506.04250*, 2025.
- [17] Daniela Gottesman and Mor Geva. Estimating knowledge in large language models without generating a single token. *arXiv preprint arXiv:2406.12673*, 2024.
- [18] Nuno M Guerreiro, Elena Voita, and André FT Martins. Looking for a needle in a haystack: A comprehensive study of hallucinations in neural machine translation. *arXiv preprint arXiv:2208.05309*, 2022.
- [19] Abhijeet Gupta, Gemma Boleda, Marco Baroni, and Sebastian Padó. Distributional vectors encode referential attributes. In Lluís Màrquez, Chris Callison-Burch, and Jian Su, editors, *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 12–21, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1002. URL <https://aclanthology.org/D15-1002/>.
- [20] Abhijeet Gupta, Gemma Boleda, Marco Baroni, and Sebastian Padó. Distributional vectors encode referential attributes. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 12–21, 2015.
- [21] John Hewitt and Percy Liang. Designing and interpreting probes with control tasks. *arXiv preprint arXiv:1909.03368*, 2019.
- [22] Lei Huang, Weijiang Yu, Weitao Ma, Weihong Zhong, Zhangyin Feng, Haotian Wang, Qianglong Chen, Weihua Peng, Xiaocheng Feng, Bing Qin, et al. A survey on hallucination in large language models: Principles, taxonomy, challenges, and open questions. *ACM Transactions on Information Systems*, 2023.
- [23] Yuheng Huang, Jiayang Song, Zhijie Wang, Shengming Zhao, Huaming Chen, Felix Juefei-Xu, and Lei Ma. Look before you leap: An exploratory study of uncertainty measurement for large language models. *arXiv preprint arXiv:2307.10236*, 2023.
- [24] Minyoung Huh, Brian Cheung, Tongzhou Wang, and Phillip Isola. The platonic representation hypothesis. *arXiv preprint arXiv:2405.07987*, 2024.
- [25] Dieuwke Hupkes, Sara Veldhoen, and Willem Zuidema. Visualisation and diagnostic classifiers’ reveal how recurrent and recursive neural networks process hierarchical structure. *Journal of Artificial Intelligence Research*, 61:907–926, 2018.

- [26] Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. Survey of hallucination in natural language generation. *ACM Computing Surveys*, 55(12):1–38, 2023.
- [27] Albert Q Jiang, Alexandre Sablayrolles, Arthur Mensch, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Florian Bressand, Gianna Lengyel, Guillaume Lample, Lucile Saulnier, et al. Mistral 7b. *arXiv preprint arXiv:2310.06825*, 2023.
- [28] Mandar Joshi, Eunsol Choi, Daniel S Weld, and Luke Zettlemoyer. Triviaqa: A large scale distantly supervised challenge dataset for reading comprehension. *arXiv preprint arXiv:1705.03551*, 2017.
- [29] Saurav Kadavath, Tom Conerly, Amanda Askell, Tom Henighan, Dawn Drain, Ethan Perez, Nicholas Schiefer, Zac Hatfield-Dodds, Nova DasSarma, Eli Tran-Johnson, et al. Language models (mostly) know what they know. *arXiv preprint arXiv:2207.05221*, 2022.
- [30] Hassane Kissane, Achim Schilling, and Patrick Krauss. Probing internal representations of multi-word verbs in large language models. In Atul Kr. Ojha, Voula Giouli, Verginica Barbu Mititelu, Mathieu Constant, Gražina Korvel, A. Seza Doğruöz, and Alexandre Rademaker, editors, *Proceedings of the 21st Workshop on Multiword Expressions (MWE 2025)*, pages 7–13, Albuquerque, New Mexico, U.S.A., May 2025. Association for Computational Linguistics. ISBN 979-8-89176-243-5. URL <https://aclanthology.org/2025.mwe-1.2/>.
- [31] Arne Köhn. What’s in an embedding? analyzing word embeddings through multilingual evaluation. In Lluís Màrquez, Chris Callison-Burch, and Jian Su, editors, *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 2067–2073, Lisbon, Portugal, September 2015. Association for Computational Linguistics. doi: 10.18653/v1/D15-1246. URL <https://aclanthology.org/D15-1246/>.
- [32] Simon Kornblith, Mohammad Norouzi, Honglak Lee, and Geoffrey Hinton. Similarity of neural network representations revisited. In *International conference on machine learning*, pages 3519–3529. PMLR, 2019.
- [33] Lorenz Kuhn, Yarin Gal, and Sebastian Farquhar. Semantic uncertainty: Linguistic invariances for uncertainty estimation in natural language generation. *arXiv preprint arXiv:2302.09664*, 2023.
- [34] Lorenz Kuhn, Yarin Gal, and Sebastian Farquhar. Semantic uncertainty: Linguistic invariances for uncertainty estimation in natural language generation, 2023. URL <https://arxiv.org/abs/2302.09664>.
- [35] Junyi Li, Xiaoxue Cheng, Xin Zhao, Jian-Yun Nie, and Ji-Rong Wen. HaluEval: A large-scale hallucination evaluation benchmark for large language models. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 6449–6464, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.397. URL <https://aclanthology.org/2023.emnlp-main.397/>.
- [36] Kenneth Li, Oam Patel, Fernanda Viégas, Hanspeter Pfister, and Martin Wattenberg. Inference-time intervention: Eliciting truthful answers from a language model. *Advances in Neural Information Processing Systems*, 36, 2024.
- [37] Nelson F Liu, Matt Gardner, Yonatan Belinkov, Matthew E Peters, and Noah A Smith. Linguistic knowledge and transferability of contextual representations. *arXiv preprint arXiv:1903.08855*, 2019.
- [38] Tianyu Liu, Yizhe Zhang, Chris Brockett, Yi Mao, Zhifang Sui, Weizhu Chen, and Bill Dolan. A token-level reference-free hallucination detection benchmark for free-form text generation. *arXiv preprint arXiv:2104.08704*, 2021.
- [39] I Loshchilov. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017.

- [40] Andrew Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies*, pages 142–150, 2011.
- [41] Sharan Maiya, Yinzhong Liu, Ramit Debnath, and Anna Korhonen. Improving preference extraction in llms by identifying latent knowledge through classifying probes. *arXiv preprint arXiv:2503.17755*, 2025.
- [42] Potsawee Manakul, Adian Liusie, and Mark JF Gales. Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models. *arXiv preprint arXiv:2303.08896*, 2023.
- [43] Samuel Marks and Max Tegmark. The geometry of truth: Emergent linear structure in large language model representations of true/false datasets. *arXiv preprint arXiv:2310.06824*, 2023.
- [44] Rowan Hall Maudslay, Josef Valvoda, Tiago Pimentel, Adina Williams, and Ryan Cotterell. A tale of a probe and a parser. *arXiv preprint arXiv:2005.01641*, 2020.
- [45] Ari Morcos, Maithra Raghu, and Samy Bengio. Insights on representational similarity in neural networks with canonical correlation. *Advances in neural information processing systems*, 31, 2018.
- [46] Luca Moschella, Valentino Maiorca, Marco Fumero, Antonio Norelli, Francesco Locatello, and Emanuele Rodolà. Relative representations enable zero-shot latent space communication. *arXiv preprint arXiv:2209.15430*, 2022.
- [47] Aviv Navon, Aviv Shamsian, Idan Achituve, Ethan Fetaya, Gal Chechik, and Haggai Maron. Equivariant architectures for learning in deep weight spaces. In *International Conference on Machine Learning*, pages 25790–25816. PMLR, 2023.
- [48] Hadas Orgad, Michael Toker, Zorik Gekhman, Roi Reichart, Idan Szpektor, Hadas Kotek, and Yonatan Belinkov. Llm know more than they show: On the intrinsic representation of llm hallucinations. *arXiv preprint arXiv:2410.02707*, 2024.
- [49] Henry Papadatos and Rachel Freedman. Linear probe penalties reduce llm sycophancy. *arXiv preprint arXiv:2412.00967*, 2024.
- [50] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, et al. Pytorch: An imperative style, high-performance deep learning library. *Advances in neural information processing systems*, 32, 2019.
- [51] Yifu Qiu, Yftah Ziser, Anna Korhonen, Edoardo Ponti, and Shay Cohen. Detecting and mitigating hallucinations in multilingual summarisation. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 8914–8932, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.551. URL <https://aclanthology.org/2023.emnlp-main.551/>.
- [52] Yifu Qiu, Zheng Zhao, Yftah Ziser, Anna Korhonen, Edoardo Maria Ponti, and Shay Cohen. Spectral editing of activations for large language model alignment. *Advances in Neural Information Processing Systems*, 37:56958–56987, 2024.
- [53] Miriam Rateike, Celia Cintas, John Wamburu, Tanya Akumu, and Skyler Speakman. Weakly supervised detection of hallucinations in llm activations. *arXiv preprint arXiv:2312.02798*, 2023.
- [54] Vipula Rawte, Swagata Chakraborty, Agnibh Pathak, Anubhav Sarkar, SM Tonmoy, Aman Chadha, Amit P Sheth, and Amitava Das. The troubling emergence of hallucination in large language models—an extensive definition, quantification, and prescriptive remediations. *arXiv preprint arXiv:2310.04988*, 2023.

- [55] Pranab Sahoo, Prabhask Meharia, Akash Ghosh, Sriparna Saha, Vinija Jain, and Aman Chadha. A comprehensive survey of hallucination in large language, image, video and audio foundation models. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 11709–11724, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-emnlp.685. URL <https://aclanthology.org/2024.findings-emnlp.685/>.
- [56] Yeongbin Seo, Dongha Lee, and Jinyoung Yeo. Detecting hallucination before answering: Semantic compression through instruction, 2025. URL <https://openreview.net/forum?id=YF0g1LUGG1>.
- [57] Xing Shi, Inkit Padhi, and Kevin Knight. Does string-based neural MT learn source syntax? In Jian Su, Kevin Duh, and Xavier Carreras, editors, *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1526–1534, Austin, Texas, November 2016. Association for Computational Linguistics. doi: 10.18653/v1/D16-1159. URL <https://aclanthology.org/D16-1159/>.
- [58] Xing Shi, Inkit Padhi, and Kevin Knight. Does string-based neural mt learn source syntax? In *Proceedings of the 2016 conference on empirical methods in natural language processing*, pages 1526–1534, 2016.
- [59] Adi Simhi, Jonathan Herzig, Idan Szpektor, and Yonatan Belinkov. Constructing benchmarks and interventions for combating hallucinations in llms. *arXiv preprint arXiv:2404.09971*, 2024.
- [60] Aviv Slobodkin, Omer Goldman, Avi Caciularu, Ido Dagan, and Shauli Ravfogel. The curious case of hallucinatory (un) answerability: Finding truths in the hidden states of over-confident large language models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 3607–3625, 2023.
- [61] Ben Snyder, Marius Moisesescu, and Muhammad Bilal Zafar. On early detection of hallucinations in factual question answering. In *Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*, pages 2721–2732, 2024.
- [62] SM Tonmoy, SM Zaman, Vinija Jain, Anku Rani, Vipula Rawte, Aman Chadha, and Amitava Das. A comprehensive survey of hallucination mitigation techniques in large language models. *arXiv preprint arXiv:2401.01313*, 2024.
- [63] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- [64] Neeraj Varshney, Wenlin Yao, Hongming Zhang, Jianshu Chen, and Dong Yu. A stitch in time saves nine: Detecting and mitigating hallucinations of llms by validating low-confidence generation. *arXiv preprint arXiv:2307.03987*, 2023.
- [65] Dimitri Von Rütte, Sotiris Anagnostidis, Gregor Bachmann, and Thomas Hofmann. A language model’s guide through latent space. *arXiv preprint arXiv:2402.14433*, 2024.
- [66] An Yang, Baosong Yang, Binyuan Hui, Bo Zheng, Bowen Yu, Chang Zhou, Chengpeng Li, Chengyuan Li, Dayiheng Liu, Fei Huang, Guanting Dong, Haoran Wei, Huan Lin, Jialong Tang, Jialin Wang, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Ma, Jin Xu, Jingren Zhou, Jinze Bai, Jinzheng He, Junyang Lin, Kai Dang, Keming Lu, Keqin Chen, Kexin Yang, Mei Li, Mingfeng Xue, Na Ni, Pei Zhang, Peng Wang, Ru Peng, Rui Men, Ruize Gao, Runji Lin, Shijie Wang, Shuai Bai, Sinan Tan, Tianhang Zhu, Tianhao Li, Tianyu Liu, Wenbin Ge, Xiaodong Deng, Xiaohuan Zhou, Xingzhang Ren, Xinyu Zhang, Xipin Wei, Xuancheng Ren, Yang Fan, Yang Yao, Yichang Zhang, Yu Wan, Yunfei Chu, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zhihao Fan. Qwen2 technical report. *arXiv preprint arXiv:2407.10671*, 2024.
- [67] Zhilin Yang, Peng Qi, Saizheng Zhang, Yoshua Bengio, William W Cohen, Ruslan Salakhutdinov, and Christopher D Manning. Hotpotqa: A dataset for diverse, explainable multi-hop question answering. *arXiv preprint arXiv:1809.09600*, 2018.

- [68] Fan Yin, Jayanth Srinivasa, and Kai-Wei Chang. Characterizing truthfulness in large language model generations with local intrinsic dimension. *arXiv preprint arXiv:2402.18048*, 2024.
- [69] Mert Yuksekgonul, Varun Chandrasekaran, Erik Jones, Suriya Gunasekar, Ranjita Naik, Hamid Palangi, Ece Kamar, and Besmira Nushi. Attention satisfies: A constraint-satisfaction lens on factual errors of language models. *arXiv preprint arXiv:2309.15098*, 2023.
- [70] Zining Zhu, Soroosh Shahtalebi, and Frank Rudzicz. Predicting fine-tuning performance with probing. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 11534–11547, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.793. URL <https://aclanthology.org/2022.emnlp-main.793/>.
- [71] Andy Zou, Long Phan, Sarah Chen, James Campbell, Phillip Guo, Richard Ren, Alexander Pan, Xuwang Yin, Mantas Mazeika, Ann-Kathrin Dombrowski, et al. Representation engineering: A top-down approach to ai transparency. *arXiv preprint arXiv:2310.01405*, 2023.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [Yes]

Justification: All claims are justified in Sections 4 and 5.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [Yes]

Justification: Yes, see Section 6.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: The paper does not include any formal, explicit theoretical result.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: All experimental details are provided in Section 5 and Appendix A.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: The code to reproduce all our experiments is provided in <https://github.com/BarSGuy/ACT-ViT>.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: All necessary experimental details are available in Section 5 and Appendix A.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: As stated during submission, we committed to including error bars in the final version upon acceptance. We have now added results averaged over 3 random seeds with 1-sigma error bars, reported in Appendix A.3.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)

- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: All necessary experimental details are available in Section 5 and

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: This paper does not violate any aspect of the code of ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: Please refer to Appendix D.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [\[Yes\]](#)

Justification: The paper poses no such risks.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [\[Yes\]](#)

Justification: All baselines as well as accessed code and data repositories have been credited throughout Section 5 and Appendix A. For licenses and terms of use please refer to Appendix A.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.

- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset's creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: The paper does not release new assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: The paper does not involve crowdsourcing nor research with human subjects

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [NA]

Justification: The paper studies the task of Hallucination Detection in LLMs, but the core method development in this research does not involve LLMs as any important, original, or non-standard components.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

A Extended Experimental Section

Our experiments were conducted using the PyTorch [50] framework (License: BSD), using a single NVIDIA L-40 GPU for all experiments. We use a fixed batch size of 128 for all experiments, other than the ones with ACT-ViT(s), ACT-MLP(s), where we used a batch size of 64. We used 4 heads in the transformer part of ViT for all experiments. Hyperparameter tuning was performed utilizing the Weight and Biases framework [9] – see Appendix A.1.

Optimizer and Schedulers. For all datasets, we use the AdamW optimizer [39] in combination with a cosine learning rate scheduler, incorporating a warm-up phase over the first 10% of training epochs.

LLMs. We consider the following LLMs for our experiments:

1. **Mistral-7b-instruct-v0.2** [27] (License: Apache-2.0). Referred to as Mis-7B in the main text and accessed through the Hugging Face interface at <https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3>.
2. **Llama-3-8b-Instruct** [63] (License: Llama-3⁵). Referred to as LLaMa-8B in the main text and accessed through the Hugging Face interface at <https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct3>.
3. **Qwen-2.5-7b-Instruct** (License: Apache-2.0): Referred to as Qwen-7B in the main text and accessed through the Hugging Face interface at <https://huggingface.co/Qwen/Qwen2.5-7B-Instruct>.

Generating Activation Tensors. Given a large language model (LLM) M and an output sequence of N tokens, we define the *activation tensor* $\mathbf{A} \in \mathbb{R}^{L_M \times N \times D_M}$, where L_M is the number of layers in M , and D_M is the hidden dimension. Let $\mathbf{A}^{(l)} := \mathbf{A}[l, :, :]$ denote the hidden representations at the l -th layer across the entire sequence. In a standard transformer architecture, these representations are computed as:

$$\mathbf{A}^{(l)} = \mathbf{A}^{(l-1)} + \left[\text{ReLU} \left(\text{Attn}(\mathbf{A}^{(l-1)}) \mathbf{W}_l^1 + \mathbf{b}_l^1 \right) \right] \mathbf{W}_l^2 + \mathbf{b}_l^2, \quad (1)$$

where Attn denotes the output of the multi-head attention mechanism, followed by batch normalization. The matrices $\mathbf{W}_l^1, \mathbf{W}_l^2 \in \mathbb{R}^{D_M \times D_M}$ and biases $\mathbf{b}_l^1, \mathbf{b}_l^2 \in \mathbb{R}^{D_M}$ correspond to the feed-forward subnetwork at layer l . Throughout this paper, we use the term *activation tensor* to refer to $\mathbf{A}$ as defined in Equation (1).

A.1 HyperParameters

This section outlines the hyperparameter search performed for our experiments. We employ the same hyperparameter grid for both our primary model, ACT-ViT, and our proposed baseline, ACT-MLP⁶. Hyperparameter grid search is performed to optimize the AUC on the validation set. The best hyperparameters are selected based on the run that achieves the highest validation AUC, for each of our two proposed methods, namely ACT-ViT, and ACT-MLP. The hyperparameter grids used for all experiments are outlined below, corresponding to each experimental setup:

1. Training on a single LLM-specific dataset – see Table 3.
2. Joint training on all 15 datasets simultaneously – see Table 4.
3. Leave-one-out training (excluding 1 out of 15 datasets) – upper part of Table 5.
4. Low-data regime adaptation on the held-out dataset – lower part of Table 5. “–” refers to slot which are inapplicable, or taken from the pre-trained model.
5. Leaving out one LLM (excluding 5 out of 15 LLM-dataset combinations) – see Table 6.

For the probing baselines—specifically $\text{Token}[n]$ for $n \in \mathcal{N}$ (see Section 4) and $\text{Probe}[*]$ —we performed a grid search over inverse regularization strengths $C \in \{10000, 100, 1.0, 0.01, 0.0001\}$. For each token probe, we selected the best-performing model based on validation set performance, corresponding to the optimal value of C . In the case of $\text{Probe}[*]$, we additionally selected the best token position using the validation set.

⁵<https://huggingface.co/meta-llama/Meta-Llama-3-8B/blob/main/LICENSE>

⁶The patch size parameter does not apply to these baselines, as it is not part of their configuration.

Table 3: Hyperparameter search grid for ACT-ViT(s) and ACT-MLP(s), for each of the 15 LLM-dataset combinations.

Hyperparameter Search Grid for each of the 15 LLM-dataset combinations	
Number of layers	{1, 3}
Learning rate	0.001
Embedding size	{128, 1024}
Epochs	15
Dropout	0.3
Weight Decay	{1, 0.001}
Patch Size	{(1, 1), (8, 1), (4, 2)}

Table 4: Hyperparameter search grid for ACT-ViT and ACT-MLP, in the setting where training is performed jointly across all 15 LLM-dataset combinations.

Hyperparameter Search Grid for joint-training of the 15 LLM-dataset combinations	
Number of layers	3
Learning rate	{0.001, 0.0005}
Embedding size	128
Epochs	5
Dropout	0.3
Weight Decay	{10, 0.001}
Patch Size	{(1, 1), (1, 2), (1, 4), (2, 1), (4, 1)}

Table 5: Hyperparameter search grid used for ACT-ViT and ACT-MLP when trained on the combined set of all 14 LLM datasets, in the “leaving one dataset out” setup. “–” denotes slots that are inapplicable, as their values are inherited from the pre-trained model.

Num. layers	Learning rate	Embedding size	Epochs	Dropout	Weight Decay	Patch size
Pre training (and Zero-shot)						
3	0.001	128	15	0.3	0.001	(1, 1)
Low-data regime LA adaptation (over {5%, 10%, 20%, 50%, 100%} of 10,000 test samples)						
–	0.001	–	5	–	0.001	–

Table 6: Hyperparameter search grid used for ACT-ViT and ACT-MLP when trained on the combined set of 10 LLM datasets, in the “leaving one LLM out” setup. “–” denotes slots that are inapplicable, as their values are inherited from the pre-trained model.

Num. layers	Learning rate	Embedding size	Epochs	Dropout	Weight Decay	Patch size
Pre training						
{3, 5}	0.001	128	5	0.3	0.001	{(1, 1), (8, 1), (4, 2)}
LA Adaptation						
–	0.001	–	15	–	{0.1, 0.01, 10, 20}	–

A.2 Dataset Description

In this section, we provide an overview of the five datasets used in our analysis; we mostly follow the framework given in [48] in constructing the datasets. We aimed to cover diverse tasks, reasoning skills, and datasets, highlighting each one’s unique value and how it complements the rest.

For all datasets, we used a consistent split of 10,000 training samples and 10,000 test samples, unless otherwise specified. From the 10,000 training samples, 20% (i.e., 2,000) were selected in a stratified manner for validation, using a fixed random seed of 42.

1. **HotpotQA with and without context** (License: CC-BY-SA-4.0) [67]: HotpotQA is a multi-hop question answering dataset featuring diverse questions that require reasoning across multiple sources. Each instance includes supporting Wikipedia documents. We use two settings in our analysis: (1) *Without context*, where questions are presented alone, testing factual recall and reasoning; and (2) *With context*, where supporting documents are provided, emphasizing the model’s ability to leverage contextual information effectively.
2. **Movies** [48] (License: MIT): We use this dataset to evaluate generalization in scenarios regarding movies involving factual inaccuracies (i.e., hallucinations). This dataset contains 7857 test samples.
3. **IMDB** (originally released with no known license by Maas et al. [40]): This dataset consists of movie reviews for sentiment classification. Following the method in [48], we employed a one-shot prompt to help the large language model (LLM) apply the predefined sentiment labels accurately.
4. **TriviaQA** (originally released with no known license by [28]): A dataset of trivia question-answer pairs presented to the LLM without any supporting context, relying only on its internal parametric knowledge. Multiple acceptable answer variants are provided to facilitate automatic evaluation of response accuracy.

A.3 Additional Results

Below in Table 7 we provide a comparison of ACT-ViT with LOS-Net.

Table 7: Comparison of ACT-ViT with LOS-Net. For LOS-Net, we report the 1-sigma error-bars. Best is in **Bold**.

Method	HotpotQA	IMDB	Movies	HotpotQA	IMDB	Movies	HotpotQA	IMDB	Movies
	Mis-7B			LlaMa-8B			Qwen-7B		
LOS-Net	72.92 $\pm$ 0.45	94.73 $\pm$ 0.58	72.20 $\pm$ 0.66	72.60 $\pm$ 0.34	90.57 $\pm$ 0.28	77.43 $\pm$ 0.66	73.71 $\pm$ 1.21	88.19 $\pm$ 0.88	88.01 $\pm$ 0.39
ACT-ViT	84.33	97.03	79.63	82.73	94.12	84.81	87.62	96.22	95.08

ACT-ViT performance average over three seeds. As outlined in the NeurIPS paper checklist, we provide additional results for ACT-ViT over the datasets and tasks provided Table 1, where we rerun ACT-ViT with three random seeds and report the mean and standard deviation. Those results are provided in Table 8.

Table 8: ACT-ViT AUC HD performance averaged over three seeds with 1-sigma error bars.

	HQA	Movies	HQA-Wc	IMDB	TriviaQA
Mis-7B	84.48 $\pm$ 0.28	79.64 $\pm$ 0.25	69.87 $\pm$ 0.63	97.09 $\pm$ 0.17	84.18 $\pm$ 0.57
LlaMa-8B	82.45 $\pm$ 0.36	84.05 $\pm$ 0.58	71.82 $\pm$ 0.34	93.57 $\pm$ 0.34	85.25 $\pm$ 0.35
Qwen-7B	88.03 $\pm$ 0.32	95.25 $\pm$ 0.14	78.23 $\pm$ 0.59	96.24 $\pm$ 0.05	91.12 $\pm$ 0.10

A.4 Run-Time

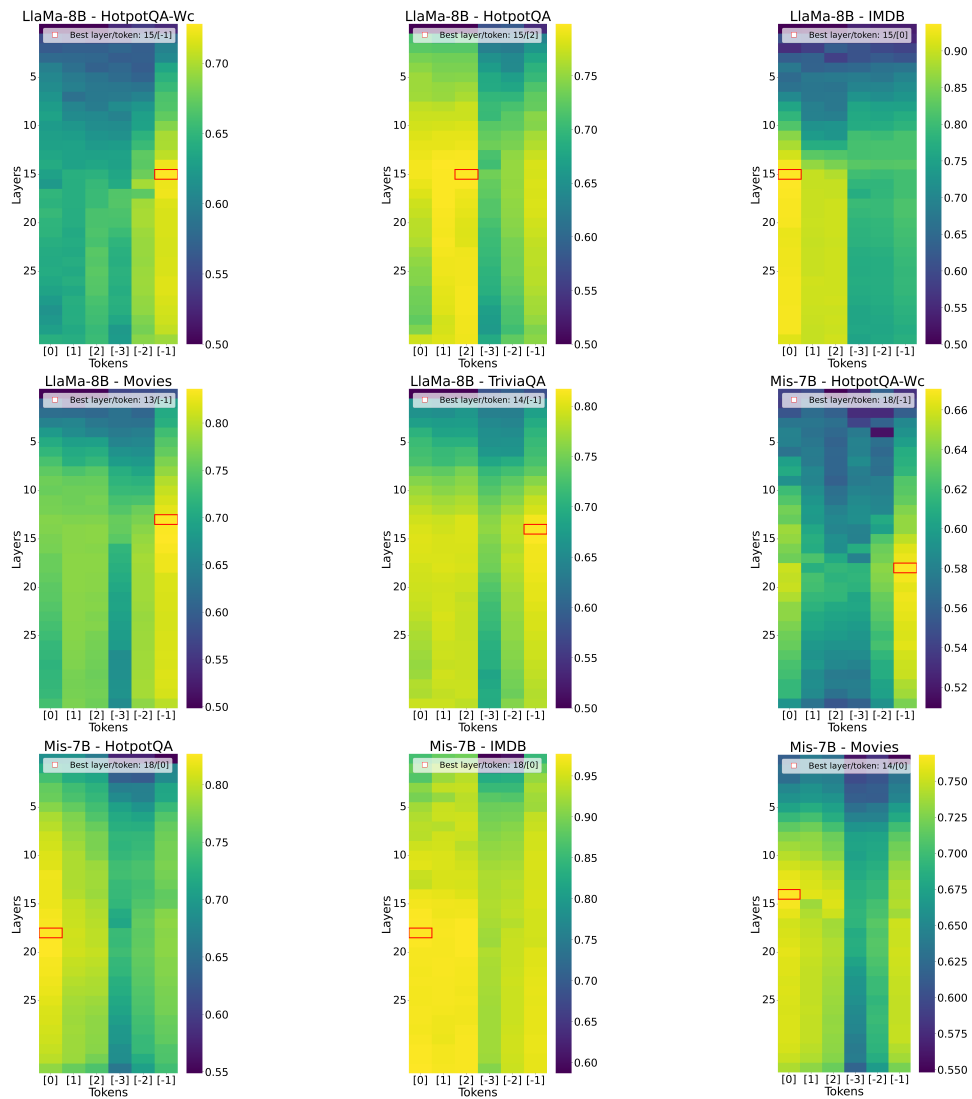
Table 9: Training time (in minutes [m] and seconds [s]) for Probe[*] and ACT-ViT across all 15 LLM–dataset combinations. Each ACT-ViT training run was performed on a single NVIDIA L-40 GPU.

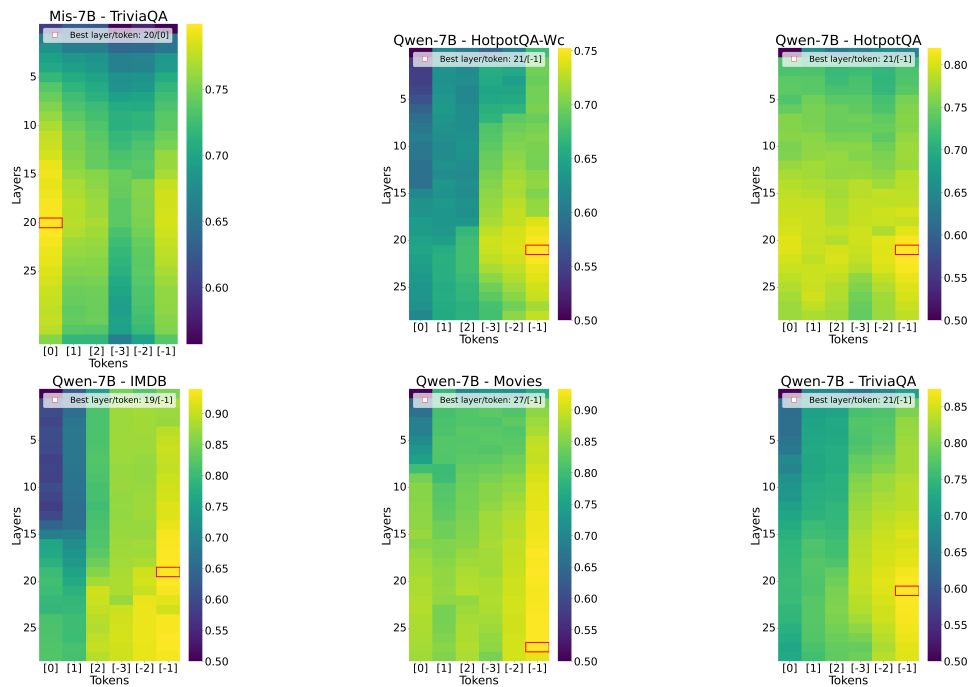
LLM	Method	HotpotQA	Movies	HQA-Wc	IMDB	TriviaQA
Mis-7B	Probe[*]	2[m] 45[s]	6[m] 23[s]	1[m] 41[s]	1[m] 38[s]	1[m] 50[s]
	ACT-ViT	13[m] 2[s]	11[m] 28[s]	12[m] 49[s]	14[m] 17[s]	12[m] 42[s]
LlaMa-8B	Probe[*]	2[m] 50[s]	2[m] 5[s]	1[m] 54[s]	2[m] 22[s]	2[m] 36[s]
	ACT-ViT	13[m] 48[s]	27[m] 5[s]	16[m] 34[s]	13[m] 1[s]	27[m] 21[s]
Qwen-7B	Probe[*]	2[m] 0[s]	1[m] 43[s]	1[m] 51[s]	1[m] 39[s]	1[m] 53[s]
	ACT-ViT	10[m] 29[s]	13[m] 12[s]	11[m] 49[s]	11[m] 30[s]	10[m] 46[s]

We present the run-time of ACT-ViT(s), on a single NVIDIA L-40 GPU, compared with probing classifiers, on each of the 15 LLM-dataset combinations considered in the paper; see Table 9.

A.5 Layer/Token Visualizations

Below we present the layer-token heatmaps, corresponding to each of the 15 LLM-dataset combination considered in our paper.





A.6 Low-Data Regime Adaptation

Below, we present additional results in the low-data training regime for all 15 LLM–dataset combinations considered in our paper.

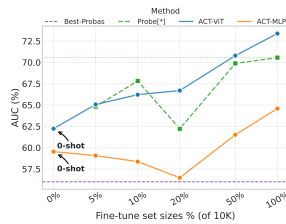


Figure 6: LLaMa-8B – HotpotQA-Wc

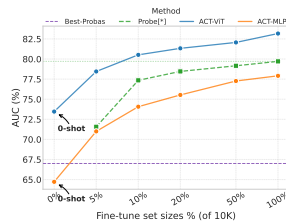


Figure 7: LLaMa-8B – HotpotQA

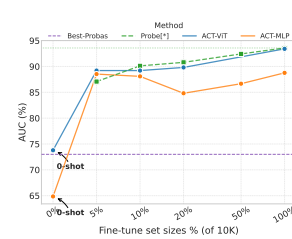


Figure 8: LLaMa-8B – IMDB

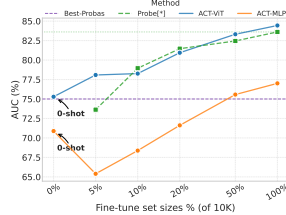


Figure 9: LLaMa-8B – Movies

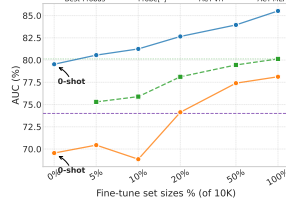


Figure 10: LLaMa-8B – TriviaQA

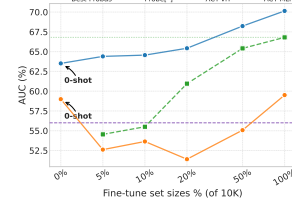


Figure 11: Mis-7B – HotpotQA-Wc

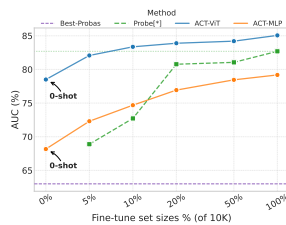


Figure 12: Mis-7B – HotpotQA

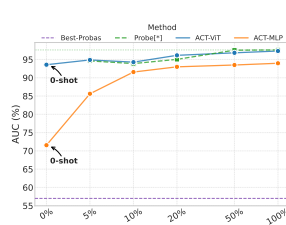


Figure 13: Mis-7B – IMDB

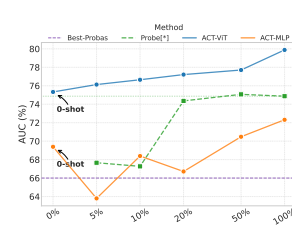


Figure 14: Mis-7B – Movies

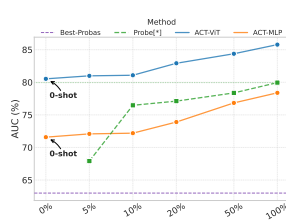


Figure 15: Mis-7B – TriviaQA

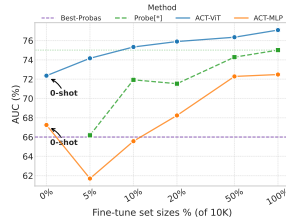


Figure 16: Qwen-7B – HotpotQA-Wc

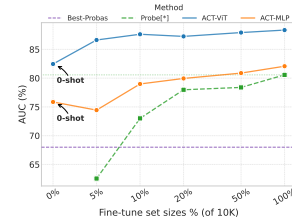


Figure 17: Qwen-7B – HotpotQA

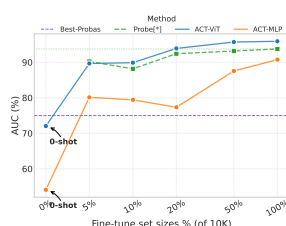


Figure 18: Qwen-7B – IMDB

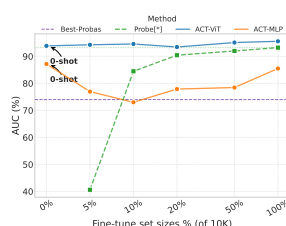


Figure 19: Qwen-7B – Movies

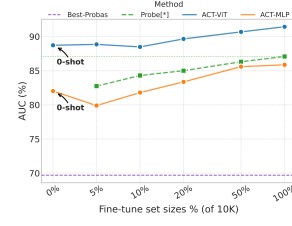


Figure 20: Qwen-7B – TriviaQA

B Pooling Algorithm

Our pooling algorithm is presented in Algorithm 1.

Algorithm 1 Pooling

Require: Tensor $\mathbf{A} \in \mathbb{R}^{L_M \times N \times D_M}$, target sizes L_p, N_p

Ensure: Tensor $\mathbf{A} \in \mathbb{R}^{L_p \times N_p \times D_M}$

1: $\mathbf{A} \leftarrow \text{permute}(\mathbf{A}, [D_M, L_M, N])$

2: Pad $\mathbf{A}$ so that L_M and N are divisible by L_p and N_p

3: Compute patch sizes: $f_L = \frac{L_{\text{pad}}}{L_p}, f_N = \frac{N_{\text{pad}}}{N_p}$

4: Apply pooling:

$$\mathbf{A} \leftarrow \text{F.max_pool2d}(\mathbf{A}, \text{kernel_size} = (f_L, f_N))$$

5: $\mathbf{A} \leftarrow \text{permute}(\mathbf{A}, [L_p, N_p, D_M])$

6: **return** $\mathbf{A}$

C Permutation Symmetries

Given the same number of layers and hidden dimensions, two LLMs can compute the exact same function and yet produce entirely different activation tensors. This discrepancy stems from internal symmetries in the model’s weight space. To illustrate this, we consider a simplified transformer architecture with L layers, omitting residual connections and batch normalization for clarity (though the analysis extends to those cases as well).

Recall that $\mathbf{A}^l$ is the activation tensor at layer $l \in [L]$. Let $(\mathbf{Q}_l, \mathbf{K}_l, \mathbf{V}_l)$ denote the query, key, and value matrices at layer l , computed as:

$$(\mathbf{Q}_l, \mathbf{K}_l, \mathbf{V}_l) = (\mathbf{A}^{l-1} \mathbf{W}_l^{Q_l}, \mathbf{A}^{l-1} \mathbf{W}_l^{K_l}, \mathbf{A}^{l-1} \mathbf{W}_l^{V_l}). \quad (2)$$

Assume the feed-forward network (FFN) at layer l produces output:

$$\mathbf{A}^l = \text{ReLU}(\text{Attn}(\mathbf{A}^{l-1}) \mathbf{W}_l^1 + \mathbf{b}_l^1) \mathbf{W}_l^2 + \mathbf{b}_l^2. \quad (3)$$

Now assume the model uses d -dimensional hidden features, and let $P \in \mathbb{R}^{d \times d}$ be a permutation matrix, and define the following weight transformation:

$$(\mathbf{W}_l^2, \mathbf{b}_l^2) \rightarrow (\mathbf{W}_l^2 P^\top, \mathbf{b}_l^2 P^\top), \quad (4)$$

$$(\mathbf{W}_{l+1}^{Q_{l+1}}, \mathbf{W}_{l+1}^{K_{l+1}}, \mathbf{W}_{l+1}^{V_{l+1}}) \rightarrow (P \mathbf{W}_{l+1}^{Q_{l+1}}, P \mathbf{W}_{l+1}^{K_{l+1}}, P \mathbf{W}_{l+1}^{V_{l+1}}). \quad (5)$$

Although the new weights (the right hand side) are very different, it is straightforward to verify that the permutation matrices cancel out, leaving the underlying function unchanged. However, recalling Equation (3), the activation tensors differ significantly, as the transformation permutes the feature dimension as follows:

$$\mathbf{A}[l, n, d] \rightarrow \mathbf{A}[l, n, \sigma(d)], \quad (6)$$

where σ is the permutation induced by P .

This illustrative example remarks the relevance of resorting to LLM-specific LA modules, as opposed to using a single shared linear adapter. Although padding can side-step the dimensionality problem, such a single adapter would be required to implicitly learn (to be invariant to) all feature permutations that may potentially arise ($D!$). While we note that principled approaches for handling such symmetries exist – such as designing layers that are invariant to feature permutations by design – we consider these less relevant to us given the limited number of considered LLMs. Exploring symmetry-aware architectures still remains a promising direction we envision to explore in future endeavors.

Extended Analysis to Standard Transformers Activations. The implications extend naturally to a standard transformer that includes residual connections and batch normalization. Residual connections do not affect the analysis, since in our analysis the permutation symmetry is applied uniformly across layers—the same permutation is used for all weight matrices, so the residual addition remains consistent with our analysis. Batch normalization also preserves this symmetry, as it is a permutation-equivariant operation: applying a permutation to the input features results in a correspondingly permuted output.

D Broader Impact

By enhancing the detection of hallucinations in Large Language Models, our work contributes to the responsible development and deployment of generative AI by promoting greater transparency and trust. However, we acknowledge that our findings also reveal aspects of the predictive information embedded within LLM internals. This insight could be misused by malicious actors, potentially motivating restrictions on LLM internals access and thereby slowing progress in open research.