Don't Go Breaking My LLM: The Impact of Pruning Attention Layers on Explanation Faithfulness and Confidence Calibration

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Abstract

Pruning Large Language Models (LLMs) reduces memory and inference costs by removing parts of the network, producing smaller models that retain most of their accuracy. As attention layers are the most resource-intensive parts of LLMs, pruning them is a promising compression strategy. Prior work shows that up to 33% of attention layers can be pruned with minimal accuracy loss. Nevertheless, the impact of attention pruning on model interpretability, specifically faithfulness and confidence calibration, remains unstudied. To address this gap, we study how pruning attention layers affects explanation faithfulness and confidence calibration across five LLMs and eight datasets. While the pruned models often maintain high accuracy, we find that their faithfulness and calibration often degrade. Notably, faithfulness and calibration can fluctuate significantly, even when accuracy remains stable, highlighting a misalignment between model confidence, interpretability, and accuracy. Our findings suggest that layer pruning can affect LLMs' interpretability and reliability in ways not captured by accuracy and efficiency measures alone. We recommend including explainability and calibration metrics when evaluating pruned models. The code is available at: `https://github.com/pietrotrope/Dont_Go_Breaking_My_LLM`

1 Introduction

Large Language Models (LLMs) have achieved exceptional results across tasks, yet their high computational demands make them costly to deploy. Pruning is a family of model compression techniques that reduces inference time and memory requirements by removing parts of the model, while aiming to preserve performance. A specific type of pruning is layer removal, also known as layer drop (Gromov et al., 2025; He et al., 2026), which cuts entire layers from the model. This method is simple and model agnostic, making

it relevant in current research. Layer removal in LLMs can reduce computational costs with minimal accuracy loss, especially when pruning attention layers rather than MLPs; up to 33% of attention layers can be removed without harming performance (Siddiqui et al., 2024). However, the impact of layer pruning on key aspects of interpretability, such as faithfulness (do model rationales accurately reflect the reasoning process of the model?) and confidence calibration (do predicted probabilities reflect true likelihoods?), remains underexplored (Jacovi & Goldberg, 2020; Naeini et al., 2015).

To fill this gap, we present the first systematic study of how pruning attention layers affects explanation faithfulness and confidence calibration. Specifically, we make three contributions. First, we provide the first evaluation of the impact of attention layer pruning on the faithfulness of LIME (Ribeiro et al., 2016) and Kernel SHAP (Lundberg & Lee, 2017) feature attributions, measured using comprehensiveness and sufficiency (DeYoung et al., 2020). Second, we present the first analysis of how attention layer pruning influences the alignment between model confidence and accuracy by computing the Estimated Calibration Error (ECE) (Naeini et al., 2015). Third, we relate changes in explanation faithfulness and confidence alignment to changes in model accuracy, investigating whether accuracy degradation due to attention layer pruning is a good proxy for its effects on explanation faithfulness and confidence calibration.

We find that pruning attention layers negatively affects LLMs' explanation faithfulness. Notably, changes in faithfulness are often unstable and can occur independently of changes in accuracy. For both pruned and unpruned models, we analyse the calibration between model confidence and accuracy and find that removing more layers generally causes them to follow different trends. As with faithfulness, the effect of pruning on calibration is not aligned with the effect on accuracy, highlighting the limitations of using only accuracy to evaluate pruned models. Overall, we provide novel evidence that attention layer pruning can unpredictably degrade model interpretability and confidence calibration in ways that are not captured by accuracy.

2 Related work

Model pruning is a family of compression approaches used to improve the efficiency of LLMs by removing parts of the model, such as parameters or structures (e.g., neurons, features, layers). Pruning methods aim to reduce model size, lower computational costs, and accelerate inference, while preserving the model's performance. Pruning methods can be either unstructured or structured.

Unstructured Pruning. Unstructured pruning methods remove individual parameters (weights) from a neural network without enforcing any specific sparsity pattern. There exist several unstructured pruning methods for LLMs, such as SparseGPT (Frantar & Alistarh, 2023), Wanda (Sun et al., 2024), and RIA (Zhang et al., 2024d). These methods can preserve most of the models' performance while increasing their sparsity. However, even though unstructured pruning reduces the number of parameters, it often does not lead to faster inference on standard hardware (e.g., CPUs or GPUs), since the resulting sparse patterns are irregular and hard to leverage (Li et al., 2017). Recent pruners, therefore, include a semi-structured variant, which imposes some structure on the sparsity patterns and can, in principle, enable hardware acceleration (Li et al., 2017; Frantar & Alistarh, 2023; Sun et al., 2024; Zhang et al., 2024d;b).

Structured Pruning and Layer Removal. Structured pruning methods remove entire structures, such as attention heads, neurons, or entire layers, from a neural network. Several structured pruning methods have been developed for LLMs (Ma et al., 2023; Xia et al., 2024; Michel et al., 2019; Ashkboos et al., 2024; Men et al., 2024). These methods can lead to tangible efficiency improvements; however, they tend to yield worse performance to sparsity trade-offs compared to unstructured pruning (Hu et al., 2025).

A subset of the structured pruning literature specifically targets the removal of entire layers from the network. Siddiqui et al. (2024) investigate the removal of both MLP and attention layers in decoder-based architectures, finding that pruning attention layers leads to smaller accuracy drops compared to pruning MLPs. Remarkably, up to 33% of attention layers can be removed without compromising performance on specific downstream tasks. Additionally, pruning attention layers reduces the computational cost associated with the KV-cache. In another example, Gromov et al. (2025) remove layers using the similarity between their input and output representations as a proxy for layer importance. Yet, studies on how layer pruning

Table 1: Number of samples, number of classes, and task for each dataset.

Dataset	# samples	# Classes	Task
ARC Easy	2376	4	Multiple Choice QA
ARC Challenge	1172	4	Multiple Choice QA
OpenBookQA	500	4	Multiple Choice QA
BoolQ	3270	2	Question Answering (Yes/No)
TweetEval	2000	3	Sentiment Analysis
Rotten Tomatoes	1066	2	Sentiment Analysis
SST-2	872	2	Sentiment Analysis
RTE	277	2	Natural Language Inference

Table 2: Number of parameters, number of layers, and vocabulary size for each LLM.

Model	# parameters	# layers	vocab size
Mistral 7B	7B	32	32,000
Llama-2 7B	7B	32	32,000
Llama-3 8B	8B	32	128,256
Qwen-3 4B	4B	36	151,936
Qwen-3 8B	8B	36	151,936

Table 3: Summary of the used feature attribution methods and evaluation measures.

Effectiveness	Features attribution	Faithfulness	Confidence Calibration
Accuracy	LIME	Comprehensiveness	Expected Calibration Error (ECE)
Δ Accuracy	Kernel SHAP	Sufficiency	

affects model performance have primarily focused on measures like accuracy and inference time (Men et al., 2024; He et al., 2026; Zhang et al., 2024c; Siddiqui et al., 2024; Kim et al., 2024; Song et al., 2024).

Pruned models evaluation. Most pruning studies evaluate models using accuracy and inference time (Frantar & Alistarh, 2023; Sun et al., 2024; Zhang et al., 2024d; Men et al., 2024; He et al., 2026; Zhang et al., 2024c; Siddiqui et al., 2024; Kim et al., 2024; Song et al., 2024). Other work has examined internal properties of pruned models, such as the similarity of representations across layers (Gromov et al., 2025; Song et al., 2024; Zhang et al., 2024a). Prior work also focuses on pruned models' fact recall and retrieval abilities (Jin et al., 2023), hallucinations in abstractive summarisation (Chrysostomou et al., 2024), and on inspecting the effect of pruning on models' biases and stereotypes Kirsten et al. (2025); Hooker et al. (2020), fairness (Ramesh et al., 2023), toxicity (Xu et al., 2024), lie detection (Fu et al., 2025), and safety (Hasan et al., 2024; GNVV et al., 2025). However, current research still overlooks other critical models' properties. Two such properties are faithfulness, which measures how accurately attributions capture the model's actual reasoning process (Jacovi & Goldberg, 2020; Lyu et al., 2024; Serrano & Smith, 2019; DeYoung et al., 2020; Ju et al., 2022), and confidence calibration, which measures how well the model's predicted probabilities reflect actual accuracy (Naeini et al., 2015). Both are important for developing interpretable and trustworthy AI systems.

Faithfulness and confidence calibration have been studied in the context of LLM evaluation (Jacovi & Goldberg, 2020; DeYoung et al., 2020; Guo et al., 2017; Naeini et al., 2015), but remain unexplored in the area of layer pruning. It is precisely this research gap that our work addresses.

3 Methodology

We study the effects of layer pruning, where entire layers are removed from the models. All analyses and results in this work are defined within this setting; different pruning settings (e.g., unstructured or weight-based pruning) may exhibit different behaviours. Precisely, we study if pruning entire layers in LLMs affects key model properties beyond accuracy, specifically explanation faithfulness and confidence calibration, and how these change in relation to accuracy. To this end, we evaluate accuracy, explanations' faithfulness, plausibility, and confidence calibration across five LLMs and eight datasets, progressively removing up to 16 attention layers. See Tabs. 1, 2, and 3 for a summary of the datasets, models, feature attributions, and measures of effectiveness, faithfulness of explanations, and confidence calibration in the paper.

3.1 Datasets and Language Models

Datasets. We use eight established datasets (in their default versions): ARC Easy and ARC Challenge (Clark et al., 2018), OpenBookQA (Mihaylov et al., 2018), BoolQ (Clark et al., 2019), RTE (Wang et al., 2018), the sentiment partition of TweetEval (Rosenthal et al., 2017), Rotten Tomatoes (Pang & Lee, 2005), and SST-2 (Socher et al., 2013). We use zero shot prompts available on LM Evaluation Harness (Gao et al., 2024), except for TweetEval and Rotten Tomatoes, for which we select prompt templates from promptsource

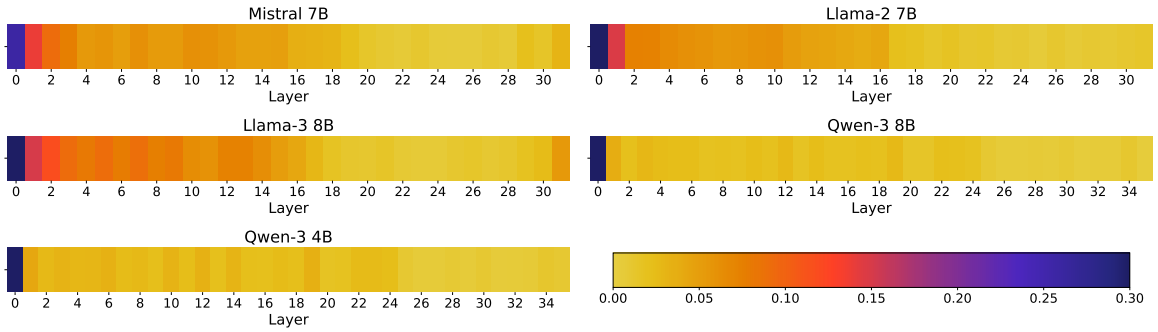

Figure 1: Importance scores of attention layers for all models.The importance scores are computed as 1 - the cosine similarity between the layer's input and output. A score of 0 means the lowest importance.

(Bach et al., 2022). See Sec. A.2 of the Appendix for the exact prompt templates. An overview of the datasets is in Tab. 1, and more details are available in Sec. A.1 of the Appendix.

Language Models. We use the 7B version of two widely used open-source models: Mistral (Jiang et al., 2023) and Llama-2 (Touvron et al., 2023), Qwen-3 in its 4B and 8B variants, and Llama-3 in its 8B variant (Yang et al., 2025; Team, 2024). An overview of the models is in Tab. 2, and more details are available in Sec. A.3 of the Appendix.

3.2 Pruning Attention Layers

In this study, we adopt a simple approach to layer pruning introduced by He et al. (2026), which removes layers from an LLM based on their relative importance. The importance score of each layer, or *block influence*, is estimated by computing the cosine similarity between the layer's input and output representations (Men et al., 2024). This calculation is based on a small amount of calibration data, i.e., data samples that are used to guide pruning. He et al. (2026) show that their pruning method is robust to the amount of calibration data, therefore, we use eight sequences of 2048 tokens sampled from the C4 dataset (Raffel et al., 2020). Layers are pruned by descending input-output similarity. Fig. 1 shows the importance score for each attention layer in all LLMs. In line with prior work (He et al., 2026; Men et al., 2024; Gromov et al., 2025), we find that early layers tend to have higher importance overall, especially for Mistral and Llama. For Qwen, this trend is less consistent, with only the first layer showing notably higher importance. Later layers remain more likely to be pruned across models. We evaluate the model at each pruning step, progressively removing one attention layer at a time, up to 16 layers. We do not consider MLP pruning in our experiments, as, unlike attention layer pruning, which largely preserves performance, removing even a few (e.g., four) MLP layers leads to substantial accuracy drops. For example, in Siddiqui et al. (2024), Mistral's MMLU (Hendrycks et al., 2021b;a) accuracy drops from over 0.6 to less than 0.3 after removing four MLP layers and to less than 0.25 (near random) after removing 12 layers, while remaining above 0.6 when removing up to 12 attention layers. Similarly, in He et al. (2026), Mistral's average accuracy across multiple tasks decreases from 0.703 to 0.534 when removing 8 MLP layers, whereas removing 8 attention layers leads to 0.697 accuracy (negligible drop). For LLaMA, removing 8 MLP layers reduces accuracy from 0.682 to 0.619, compared to 0.681 for attention removal. In addition, prior work shows that MLP layers are critical for LLM reasoning (Shao & Wu, 2025). These results indicate that removing MLP layers eliminates a critical component of the network and rapidly degrades model performance, often to near-random levels. In such settings, model outputs become unreliable, making it not meaningful to evaluate explanation quality on severely degraded predictions.

3.3 Explanation Faithfulness Evaluation

Faithfulness captures how accurately an explanation reflects the reasoning process of the model (Jacovi & Goldberg, 2020; Lyu et al., 2024). Common approaches to evaluate faithfulness require studying how removing features leads to changes in model predictions (Serrano & Smith, 2019), or evaluating different input perturbations (DeYoung et al., 2020; Ju et al., 2022). For perturbation-based measures, it is common

to compute their Area Over the Perturbation Curve (AOPC), which quantifies the average change in the scores as increasing amounts of features are removed. In this work, we adopt two AOPC-based measures introduced by DeYoung et al. (2020): *comprehensiveness* and *sufficiency*. These measures quantify how model's confidence changes when the most important input features are removed (comprehensiveness) or retained in isolation (sufficiency). We choose these measures because, in a study against four other measures, they were shown to favour more faithful explanations while being efficient to compute (Chan et al., 2022). **Comprehensiveness** is defined as:

$$\frac{1}{|\beta|+1}\sum_{k=0}^{|\beta|}[m_j(x_i) - m_j(x_i \setminus r_{ik})] \tag{1}$$

where $m_j(x_i)$ is the model's confidence in the predicted class j, given input x_i. The set β contains bins representing different proportions of top-ranked features (e.g., 10%, 20%, 30%). Lastly, r_{ik} is the most important features in bin k identified by an attribution algorithm. The measure ranges in $[-1, 1]$. A high score indicates that the most important features are crucial for the prediction, suggesting that the attributions are faithful to the model. In contrast, a negative score implies that the model becomes more confident when the important features are removed, meaning the attributions may not be faithful to the model.

Sufficiency is defined analogously, but considers the difference in the model's confidence on the full input and a perturbed input where only the important features are retained:

$$\frac{1}{|\beta|+1}\sum_{k=0}^{|\beta|}[m_j(x_i) - m_j(r_{ik})] \tag{2}$$

The measure ranges in the interval $[-1, 1]$. A high score indicates that the most important features are not sufficient for the prediction, suggesting that the explanations may not be faithful. A negative score, on the other hand, means the model becomes more confident when presented with only the most important features, supporting the claim that they are sufficient for the prediction.

We compute comprehensiveness and sufficiency (Eq. equation 1 & equation 2), using the top 10%, 20%, 30%, 40%, and 50% of tokens ranked by their attribution scores found with two attribution methods: LIME (Ribeiro et al., 2016), and Kernel SHAP (Lundberg & Lee, 2017). We use LIME and Kernel SHAP as they are based on local model-agnostic explanations, which tend to perform well on faithfulness tasks and yield more comprehensive explanations than attention-based methods (DeYoung et al., 2020). As LIME and Kernel SHAP have a stochastic component, we average all experiments over three random seeds. For computational reasons, we compute these measures on a subset of 200 randomly sampled instances per dataset.[5] For each sample, we use both the task prompt and the sample text to compute token-level importance scores.

3.4 Confidence Calibration Evaluation

A trustworthy model should exhibit confidence that closely reflects its actual accuracy (Guo et al., 2017). Such well-calibrated models are not only more interpretable, but can also enhance downstream performance (Guo et al., 2017). To quantify calibration, Naeini et al. (2015) introduced the *Expected Calibration Error (ECE)*, a measure that approximates the difference between a model's predicted confidence and its accuracy. ECE is computed by dividing predictions into M equally spaced confidence bins and calculating the weighted average of the absolute differences between accuracy and confidence within each bin:

$$\text{ECE} = \sum_{l=1}^{M}\frac{|B^l|}{n}\left|\text{acc}(B^l) - \sum_{i=1}^{B^l}\frac{m_j(B_i^l)}{|B^l|}\right| \tag{3}$$

where B^l is the l-th bin, n is the total number of samples, $\text{acc}(B^l)$ is the model's accuracy on the samples in bin l, and $m_j(B_i^l)$ is the confidence in the predicted class j, given the i-th input in bin B^l. The measure

[5]We provide the exact indices of the sampled texts together with the code

Table 4: Inter-annotator agreement per dataset measured using Jaccard distance and Krippendorff's alpha.

Dataset	Jaccard distance	Krippendorff's alpha
ARC Easy	0.666	0.664
ARC Challenge	0.365	0.378
OpenBookQA	0.443	0.385
BoolQ	0.294	0.290
TweetEval	0.384	0.352
Rotten Tomatoes	0.399	0.326
SST-2	0.426	0.391
RTE	0.402	0.409

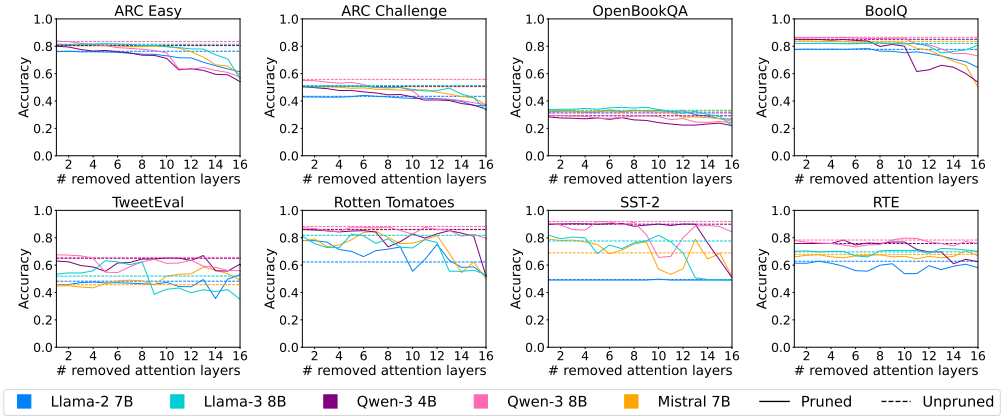

Figure 2: Accuracy of pruned and unpruned models (y axis) on eight different datasets, with varying numbers of removed attention layers (x axis). Accuracy of unpruned models is shown with dashed lines.

ranges in the interval $[0, 1]$. An ECE score near zero reflects well calibrated confidence (predicted probabilities align well with actual accuracy). Higher ECE scores reflect greater misalignment between confidence and accuracy, or less trustworthy model predictions. We measure ECE using 10 bins as per Guo et al. (2017).

3.5 Explanation Plausibility Evaluation

We study how attention layer pruning affects the plausibility of model explanations. To this end, four annotators manually annotated eight randomly sampled instances per dataset by selecting text spans they deemed relevant to the task (Hayati et al., 2021). Of these, three samples were shared across annotators to assess agreement, while the remaining five were unique to each annotator. The instructions given to the annotators are available in App. A.5. Annotations were converted to word-level relevance labels. Tab. 4 shows the Inter-annotator agreement on shared samples. Agreement is high for ARC Easy and moderate for OpenBookQA and RTE. Consistent with prior work on similar annotation protocols, for the remaining datasets, agreement is generally low (Hayati et al., 2021).

We use these annotations to evaluate the plausibility of feature attributions across both pruned and unpruned models, and across all datasets. Following prior work (Edin et al., 2024), we measure Area Under the Precision-Recall Curve (AUPRC), Precision@K, Recall@K, F1@K, and Intersection-over-Union (IoU) DeYoung et al. (2020). Except for AUPRC, which evaluates performance across multiple decision boundaries, we avoid additional classification-based metrics as they require selecting an optimal decision boundary on a validation set, which is unavailable in our setting. We consider $K \in 10, 20, 30, 40, 50\%$ of features. For IoU, we match the number of selected features to the number of features identified by annotators.

4 Results

Next, we present our experimental results. We begin by evaluating the impact of pruning on model accuracy in Sec. 4.1. We then turn to faithfulness in Sec. 4.2, examining the quality of feature attributions and

Table 5: Summary of Accuracy (Acc) and Δ Accuracy (Δ) across all datasets and models when removing 1, 4, 8, 12 and 16 attention layers. The highest drop in accuracy is bolded for each model configuration. Accuracy increases are underlined. * indicates statistical significance ($p < 0.05$) under the McNemar test. Results for the remaining configurations are available in Appendix, Tabs. 8-47.

Model	# removed	ARC Easy		ARC Challenge		OpenBookQA		BoolQ		TweetEval		Rotten Tomatoes		SST-2		RTE	
	layers	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ	Acc	Δ
Llama-2	(orig)	0.763	+0.000	0.434	+0.000	0.314	+0.000	0.777	+0.000	0.482	+0.000	0.623	+0.000	0.494	+0.000	0.628	+0.000
Llama-2	1	0.761	-0.003	0.430	-0.004	0.320	+0.006	0.777	-0.001	0.458*	**-0.025**	0.780*	+0.157	0.491	-0.003	0.614	-0.014
Llama-2	4	0.760	-0.004	0.428	-0.006	0.318	+0.004	0.779	+0.002	0.476	-0.007	0.714*	+0.091	0.491	-0.003	0.614	**-0.014**
Llama-2	8	0.742*	-0.021	0.430	-0.004	0.332	+0.018	0.765	-0.013	0.464*	-0.018	0.717*	+0.094	0.491	-0.003	0.599	**-0.029**
Llama-2	12	0.715*	**-0.048**	0.417	-0.017	0.328	+0.014	0.747*	-0.031	0.442*	-0.040	0.751*	+0.129	0.491	-0.003	0.596	-0.032
Llama-2	16	0.614*	**-0.149**	0.365*	-0.069	0.268*	-0.046	0.646*	-0.132	0.530*	+0.048	0.520*	-0.103	0.491	-0.003	0.581	-0.047
Llama-3	(orig)	0.815	+0.000	0.513	+0.000	0.332	+0.000	0.821	+0.000	0.520	+0.000	0.818	+0.000	0.776	+0.000	0.697	+0.000
Llama-3	1	0.814	-0.000	0.504	**-0.009**	0.338	+0.006	0.820	-0.000	0.534*	+0.014	0.811	-0.008	0.819*	+0.042	0.700	+0.004
Llama-3	4	0.816	+0.002	0.509	-0.004	0.346	+0.014	0.822	+0.001	0.558*	+0.038	0.727*	**-0.091**	0.799	+0.023	0.700	+0.004
Llama-3	8	0.806*	-0.009	0.497	-0.016	0.348	+0.016	0.823	+0.002	0.624*	+0.104	0.792*	**-0.026**	0.763	-0.014	0.704	+0.007
Llama-3	12	0.781*	-0.034	0.475*	-0.038	0.310	-0.022	0.800*	-0.021	0.398*	**-0.122**	0.765*	-0.053	0.690*	-0.086	0.686	-0.011
Llama-3	16	0.564*	-0.250	0.331*	-0.182	0.220*	-0.112	0.807*	-0.014	0.350*	-0.170	0.531*	**-0.287**	0.491*	-0.286	0.700	+0.004
Mistral	(orig)	0.809	+0.000	0.504	+0.000	0.326	+0.000	0.836	+0.000	0.457	+0.000	0.858	+0.000	0.689	+0.000	0.679	+0.000
Mistral	1	0.808	-0.001	0.500	-0.004	0.328	+0.002	0.836	+0.001	0.449*	-0.009	0.777*	**-0.082**	0.790*	+0.101	0.661	-0.018
Mistral	4	0.804	-0.005	0.501	-0.003	0.320	-0.006	0.835	-0.000	0.434*	-0.023	0.747*	**-0.112**	0.769*	+0.080	0.661	-0.018
Mistral	8	0.798*	-0.011	0.484*	-0.020	0.328	+0.002	0.830	-0.006	0.484*	+0.027	0.803*	**-0.055**	0.753*	+0.064	0.675	-0.004
Mistral	12	0.761*	-0.048	0.464*	-0.040	0.282*	-0.044	0.772*	-0.064	0.536*	+0.079	0.815*	-0.043	0.573*	**-0.116**	0.664	-0.014
Mistral	16	0.592*	-0.216	0.373*	-0.131	0.252*	-0.074	0.501*	-0.335	0.490	+0.033	0.500*	**-0.358**	0.517*	-0.172	0.668	-0.011
Qwen-3 8B	(orig)	0.835	+0.000	0.558	+0.000	0.312	+0.000	0.866	+0.000	0.656	+0.000	0.883	+0.000	0.919	+0.000	0.783	+0.000
Qwen-3 8B	1	0.838	+0.003	0.549	-0.009	0.296	**-0.016**	0.863	-0.002	0.675*	+0.019	0.873*	-0.009	0.908*	-0.010	0.780	-0.004
Qwen-3 8B	4	0.811*	-0.023	0.530*	-0.028	0.288	-0.024	0.862	-0.003	0.650	-0.006	0.845*	-0.038	0.856*	**-0.063**	0.758*	-0.025
Qwen-3 8B	8	0.778*	-0.056	0.497*	**-0.061**	0.290	-0.022	0.857*	-0.009	0.624*	-0.032	0.879	-0.004	0.913	-0.006	0.751*	-0.032
Qwen-3 8B	12	0.632*	**-0.203**	0.416*	-0.142	0.272	-0.040	0.811*	-0.055	0.636*	-0.020	0.861	-0.022	0.800*	-0.118	0.769	-0.014
Qwen-3 8B	16	0.576*	**-0.258**	0.373*	-0.185	0.242*	-0.070	0.729*	-0.136	0.559*	-0.097	0.796*	-0.086	0.843*	-0.076	0.758	-0.025
Qwen-3 4B	(orig)	0.805	+0.000	0.508	+0.000	0.292	+0.000	0.851	+0.000	0.650	+0.000	0.861	+0.000	0.899	+0.000	0.758	+0.000
Qwen-3 4B	1	0.800	-0.005	0.507	-0.001	0.284	-0.008	0.851	+0.000	0.630*	**-0.020**	0.860	-0.001	0.899	+0.000	0.758	+0.000
Qwen-3 4B	4	0.765*	-0.040	0.477*	-0.031	0.270	-0.022	0.845	-0.006	0.587*	**-0.064**	0.842*	-0.019	0.901	+0.002	0.758	+0.000
Qwen-3 4B	8	0.735*	-0.070	0.445*	-0.062	0.262	-0.030	0.799*	-0.052	0.644	-0.006	0.734*	**-0.128**	0.884	-0.015	0.758	+0.000
Qwen-3 4B	12	0.635*	-0.170	0.408*	-0.100	0.224*	-0.068	0.628*	**-0.223**	0.634	-0.016	0.828*	-0.033	0.900	+0.001	0.697	-0.061
Qwen-3 4B	16	0.542*	-0.263	0.340*	-0.167	0.220*	-0.072	0.537*	-0.314	0.608*	-0.042	0.521*	-0.341	0.509*	**-0.390**	0.625*	-0.134

how they relate to model predictions through comprehensiveness and sufficiency. Finally, we assess the confidence calibration of pruned and unpruned models and explore its relation to model accuracy in Sec. 4.3. A summary of our findings is available in Tab. 7

4.1 How does Pruning Attention Layers Affect Accuracy?

Fig. 2 plots model accuracy versus attention layer pruning, while Tab. 5 reports the accuracy drops across all datasets when removing 1, 4, 8, 12, and 16 layers from each model, with statistically significant changes indicated by an asterisk (*). Across models and datasets, pruning up to eight layers leads to minimal accuracy loss (under 0.06) for most cases. The only exception is Qwen-3 4B on Rotten Tomatoes, which drops by 0.13 at this pruning depth, but interestingly, its accuracy recovers with further pruning, showing less than a 0.04 drop compared to the original model when 16 layers are removed. For this same pruning range, the observed reductions are statistically significant for most cases on TweetEval and Rotten Tomatoes. In contrast, for ARC Easy, ARC Challenge, OpenBookQA, and BoolQ, accuracy degradation typically becomes statistically significant only as more layers are removed, a trend that holds consistently across all models. When 12 layers are removed, accuracy reductions remain modest: below 0.13 for Mistral 7B and Llama, and up to 0.23 for Qwen, while the number of statistically significant drops increases (see Tab. 5). On SST-2, all models except Llama-2 and Qwen-3 4B tend to exhibit statistically significant drops. Whereas, for RTE, most accuracy reductions remain not significant and typically below 3%. Overall, these results indicate

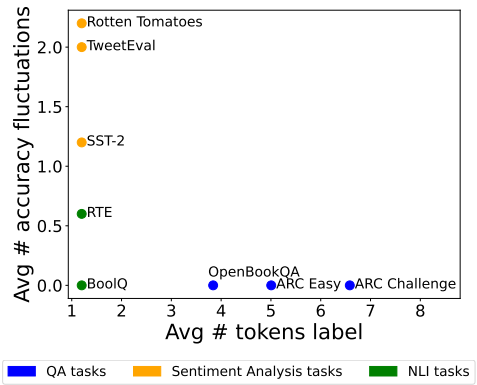

Figure 3: Accuracy fluctuations (y-axis) as pruning increases, versus average number of label tokens (x-axis). Numbers are averaged over the five LLMs.

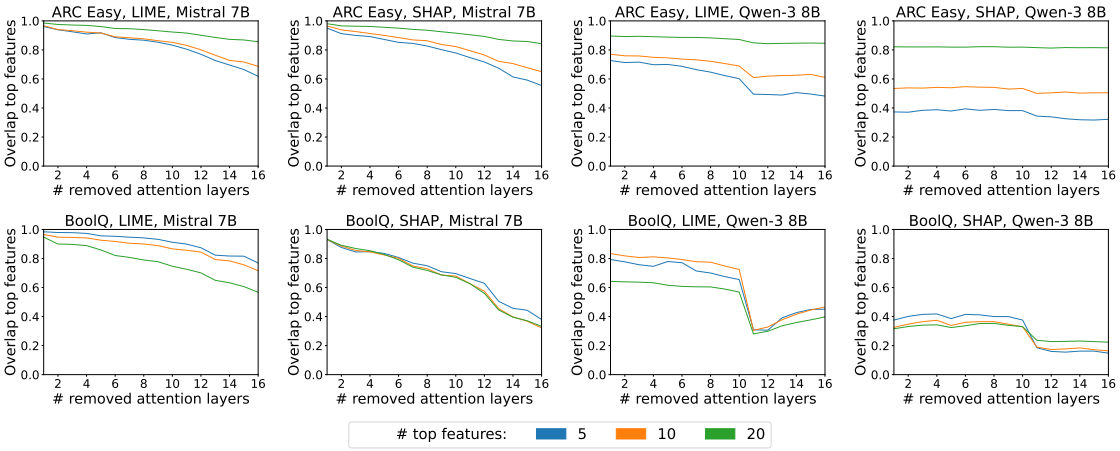

Figure 4: Overlap between the top 5, 10, and 20 LIME and Kernel SHAP features (y-axis) for pruned and unpruned Mistral 7B, as a function of the number of pruned attention layers (x-axis).

that **LLMs can be substantially pruned with only modest reductions in accuracy**. Additional results for the remaining pruning configurations are reported in the Appendix (Tabs. 8-47).

A notable pattern is the consistent accuracy reduction for all models on QA tasks (ARC Easy, ARC Challenge, and OpenBookQA) and BoolQ (the datasets in the first row of Fig. 2), whereas accuracy on sentiment analysis tasks (TweetEval, Rotten Tomatoes, and SST-2) and RTE (datasets in the second row of Fig. 2) is more unstable, with frequent accuracy fluctuations[1] as more attention layers are pruned. We hypothesise that this could be due to label length: Fig. 3 presents the average number of accuracy fluctuations per dataset (averaged over five models) versus the average number of tokens required to represent the labels. Datasets with shorter labels consistently exhibit at least one fluctuation, except for BoolQ, whereas those with longer labels show none. This could be because single-token predictions are more sensitive to pruning-induced noise, while multi-token labels allow such noise to be averaged out across tokens, resulting in more stable accuracy. Fig. 8 of Appendix B shows this in more detail.

4.2 How does Pruning Attention Layers Affect Explanation Faithfulness?

Fig. 4 shows the mean overlap between the top-k most important features ($k \in \{5, 10, 20\}$) using LIME and Kernel SHAP for pruned and unpruned Mistral 7B and Qwen-8B on ARC Easy and BoolQ (other models and datasets show overall similar trends; see Figs. 10 and 11 of Appendix B). We compute the overlap as the number of shared features divided by k,[2] where 1 means that pruned and unpruned models rely on the same top features, 0 means no shared features. Pruned and unpruned models tend to rely on similar top features. For example, considering Mistral on ARC Easy, the overlap of LIME features remains close to 1 when pruning a single layer, regardless of k. Yet, **the similarity between the most important features for pruned and unpruned models decreases as more attention layers are pruned**. This trend generalises across models and tasks, except for Mistral 7B and the NLI tasks (BoolQ and RTE). For Mistral 7B, this trend occurs in 10/16 dataset and attribution combinations; for the NLI datasets, it appears in 14/20 models and attribution combinations (see Figs. 10 and 11 in Appendix B).

We next examine comprehensiveness and sufficiency. Fig. 5 shows the relative reduction in comprehensiveness, sufficiency, and accuracy between pruned and unpruned Mistral 7B and Qwen-3 8B on ARC Challenge and SST-2 as attention layers are progressively removed (see Figs. 20-23 and 12-15 in Appendix B for the remaining relative reduction plots, as well as the absolute drops in comprehensiveness and sufficiency and their standard deviations). Complementing these visual trends, Tab. 6 summarises LIME's Comprehensive-

[1]We define a fluctuation as a 0.05 increase/decrease in accuracy that follows a prior decrease/increase. See Appendix A.4 for details on how we count the number of fluctuations.

[2]If the input contains fewer than k features, we divide by the number of features in the input.

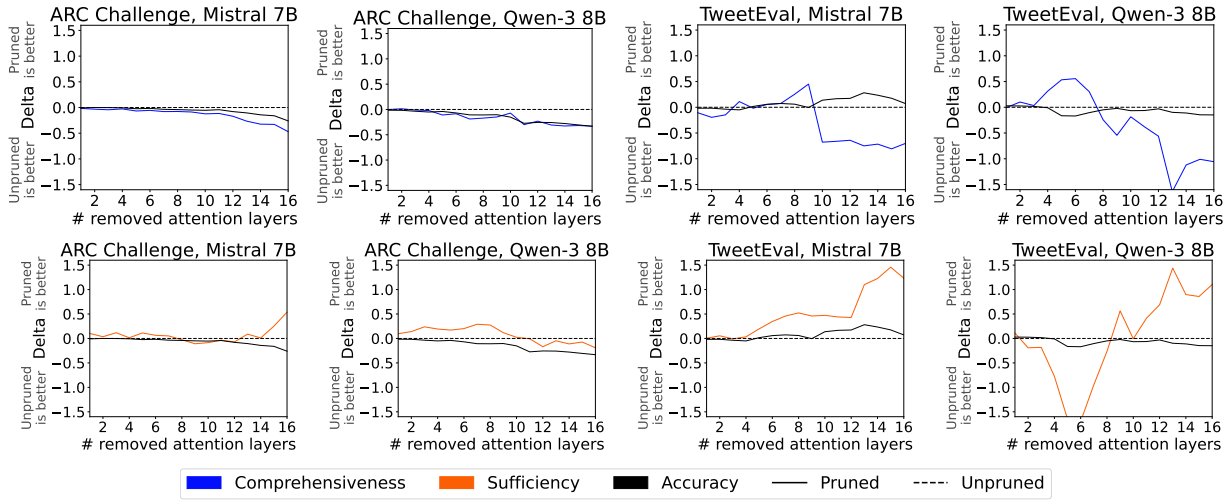

Figure 5: Relative change in LIME's comprehensiveness and sufficiency, and in accuracy (y axis) between pruned and unpruned models across attention layer pruning levels (x axis) for Mistral 7B and Qwen-3 8B. Accuracy and comprehensiveness changes are rescaled so that decreases appear lower in the plots and increases higher.

ness and Sufficiency across all datasets when removing 1, 4, 8, 12, and 16 layers from each model, with statistically significant changes indicated by an asterisk (*). Detailed additional results for other pruning configurations and for Kernel SHAP are provided in the Appendix (Tables 8-47). For both Mistral and Qwen, pruning reduces comprehensiveness from their unpruned counterparts, typically worsening it as more layers are removed. Dataset-wise, comprehensiveness drops are observed across all QA tasks (ARC Easy, ARC Challenge, and OpenBookQA), although changes in both comprehensiveness and sufficiency on these datasets do not exhibit a consistent pattern of statistical significance and vary across models and pruning configurations. In contrast, the majority of settings for BoolQ and RTE, as well as results on TweetEval, Rotten Tomatoes, and SST-2, show statistically significant changes that are largely independent of the model (see Figs. 20 and 22 in Appendix). Sufficiency also tends to decrease with pruning, though less consistently, e.g., for Llama-3, sufficiency increases as more layers are removed. This suggests that pruning attention layers can make the model's reasoning harder to explain, as comprehensiveness indicates the model relies less on the features identified as most important, while sufficiency suggests those same features are still sufficient for the prediction. This means that **pruning attention layers can lead to explanations that are less faithful to the model**. This behaviour could be partly attributed to a decrease in the model's average confidence as more attention layers are pruned. Since both comprehensiveness and sufficiency rely on the model's confidence scores, a drop in overall confidence tends to lower their values as well (see Eq. equation 1 & equation 2).[3] In addition, layers are pruned based on the magnitude of the transformations they apply to their inputs. While individually small, these transformations may still encode information important for explanations, so removing them may contribute to degrading explanation quality.

On datasets with short labels, comprehensiveness and sufficiency scores fluctuate unstably as attention layers are pruned, while they exhibit more stable trends on datasets with longer labels (see Fig. 9). This trend is aligned with accuracy (see Fig. 3), and may be explained by the fact that faithfulness measures compute average attribution scores over label tokens. On short labels (one or two tokens), the measure is sensitive to token-level variation and noise, possibly leading to increased fluctuations. In contrast, longer labels aggregate over more tokens, reducing noise and therefore fluctuation trends. However, as seen for Qwen-3 8B on TweetEval in Fig. 5 (see Figs. 20–23 for the remaining results), these fluctuations in faithfulness can be notably more pronounced than those observed in accuracy, indicating that **pruning attention layers can lead to unstable fluctuations in explanation faithfulness that do not consistently mirror**

[3]While we initially considered that this might be due to the different bins used to compute these metrics, we find that each bin has a similar pattern (see Figs. 1619 in Appendix B).

Table 6: Summary of Comprehensiveness and Sufficiency (LIME) across all datasets and models when removing 1, 4, 8, 12 and 16 attention layers. * indicates statistical significance ($p < 0.05$) under the Wilcoxon test. All LIME results and results for Kernel SHAP are available in Appendix, Tabs. 8-47.

Model	# rem.	ARC Easy		ARC Challenge		OpenBookQA		BoolQ		RTE		TweetEval		Rotten Tomatoes		SST-2	
	layers	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.	Comp.	Suff.
Llama-2	(orig)	0.233	0.190	0.255	0.140	0.245	0.160	0.282	0.092	0.092	0.040	0.072	0.133	0.092	0.128	0.108	0.052
Llama-2	1	0.234	0.189	0.253	0.140	0.247	0.162	0.267*	0.105*	0.098*	0.023*	0.038*	0.048*	0.046*	0.038*	0.200*	0.097*
Llama-2	4	0.235	0.180	0.258	0.151	0.250	0.171	0.294*	0.104*	0.153*	0.014*	0.017*	0.123	0.044*	0.098	0.233*	0.074*
Llama-2	8	0.248*	0.204*	0.244	0.162*	0.243	0.184*	0.112*	0.072	0.179*	0.056*	0.110*	0.095*	0.052*	0.041*	0.123*	-0.081*
Llama-2	12	0.215*	0.229*	0.216*	0.167*	0.221*	0.185*	0.076*	0.048*	0.217*	0.187*	0.052	-0.035*	-0.067*	-0.110*	-0.012*	-0.110*
Llama-2	16	0.200*	0.208*	0.194*	0.160*	0.162*	0.168*	-0.004*	-0.042*	0.209*	0.083*	0.006*	-0.045*	0.072*	-0.132*	0.246*	0.115*
Llama-3	(orig)	0.200	0.126	0.222	0.092	0.237	0.139	0.384	0.127	0.141	0.143	0.016	0.166	0.106	0.093	0.105	0.097
Llama-3	1	0.165*	0.153*	0.209	0.109*	0.176*	0.193*	0.088*	0.349*	0.078*	0.105*	0.036*	0.179	0.097	0.082	0.092*	0.090
Llama-3	4	0.203	0.126	0.229	0.102	0.244	0.150*	0.342*	0.125	0.135	0.118*	0.032*	0.156	0.086	0.059*	0.062*	0.051*
Llama-3	8	0.197	0.121	0.239	0.113	0.235	0.163*	0.336*	0.116*	0.167*	0.117*	0.217*	0.191	0.111	0.104	0.123*	0.107
Llama-3	12	0.207	0.132	0.209	0.100	0.195*	0.136	0.333*	0.123	0.130	0.108*	0.247*	0.167	0.081*	0.079	0.160*	0.135*
Llama-3	16	0.123*	0.070*	0.147*	0.085	0.111*	0.068*	0.373	0.110*	0.224*	0.170*	0.272*	0.223*	0.163*	0.174*	0.238*	0.248*
Mistral	(orig)	0.266	0.155	0.278	0.141	0.259	0.171	0.344	0.145	0.152	0.124	0.214	0.464	0.097	0.111	0.110	0.126
Mistral	1	0.276*	0.160*	0.273*	0.136	0.259	0.171	0.347*	0.150*	0.159	0.119*	0.191*	0.462*	0.100	0.109	0.049*	0.029*
Mistral	4	0.278*	0.160*	0.271	0.144	0.260	0.176	0.334	0.154*	0.173*	0.117*	0.238*	0.448*	0.079	0.033*	0.042*	0.006*
Mistral	8	0.280*	0.160	0.257*	0.147	0.258	0.182*	0.316*	0.157*	0.157	0.120*	0.268*	0.221*	0.098	0.076*	0.047*	0.029*
Mistral	12	0.270*	0.174*	0.231*	0.137	0.218*	0.155	0.195*	0.140	0.149	0.115*	0.077*	0.265*	0.192*	0.155*	0.269*	0.217*
Mistral	16	0.213*	0.155	0.148*	0.091*	0.139*	0.115*	-0.003*	0.053*	0.134	0.116	0.064*	-0.108*	0.026*	0.069*	0.095	0.005*
Qwen-3 8B	(orig)	0.232	0.155	0.273	0.122	0.214	0.136	0.603	0.211	0.328	0.321	0.228	0.230	0.347	0.367	0.354	0.367
Qwen-3 8B	1	0.238	0.146	0.273	0.110*	0.213	0.119	0.596	0.151*	0.306*	0.316	0.227*	0.204	0.350	0.376*	0.355	0.367
Qwen-3 8B	4	0.234	0.155	0.268	0.098*	0.200	0.119	0.545*	0.174*	0.276*	0.286*	0.300*	0.408*	0.335*	0.376	0.298*	0.308*
Qwen-3 8B	8	0.253	0.177	0.227*	0.088*	0.171*	0.086*	0.546*	0.232*	0.238*	0.260*	0.173*	0.290*	0.384*	0.339*	0.359	0.328*
Qwen-3 8B	12	0.211	0.181	0.210*	0.142	0.134*	0.093*	0.410*	0.387*	0.291*	0.318	0.100*	0.072*	0.323	0.290*	0.310*	0.274*
Qwen-3 8B	16	0.197	0.164	0.183*	0.145	0.151*	0.086*	0.396*	0.323*	0.251*	0.272*	-0.013*	-0.024*	0.262*	0.218*	0.280*	0.216*
Qwen-3 4B	(orig)	0.236	0.146	0.273	0.126	0.206	0.126	0.476	0.248	0.317	0.308	0.180	0.155	0.437	0.332	0.391	0.350
Qwen-3 4B	1	0.233	0.137*	0.268	0.137*	0.200	0.124	0.477	0.264*	0.313	0.309	0.269*	0.262*	0.429*	0.339*	0.392	0.354
Qwen-3 4B	4	0.214	0.130	0.266	0.161*	0.191*	0.116	0.420*	0.355*	0.283*	0.319*	0.225*	0.323*	0.377*	0.317	0.376*	0.343
Qwen-3 4B	8	0.208*	0.136	0.239	0.131	0.163*	0.120	0.420*	0.251	0.302	0.384*	0.083*	0.101*	0.198*	0.289*	0.329*	0.298*
Qwen-3 4B	12	0.161*	0.126	0.214*	0.115	0.149*	0.077*	0.220*	0.147*	0.247*	0.241*	0.041*	-0.008*	0.272*	0.272*	0.335*	0.328
Qwen-3 4B	16	0.126*	0.092*	0.149*	0.063*	0.110*	0.050*	0.164*	0.140*	0.203*	0.240*	0.071*	0.058*	0.272*	0.254*	0.309*	0.286*

changes in model accuracy. We hypothesise that layer pruning can reduce reliance on both informative and noisy features; however, this effect is not uniform across layers. Depending on which layers are removed, pruning may differentially affect informative and noisy signals, leading to non-monotonic behaviour and the observed fluctuations that do not necessarily align with accuracy drops.

4.3 How does Pruning Attention Layers Affect Confidence Calibration?

Since both comprehensiveness and sufficiency involve confidence, faithfulness may be influenced by model confidence. This raises a question: how well does confidence align with accuracy? To explore this, we next examine confidence calibration, which measures the alignment between predicted confidence and accuracy.

The first row of Fig. 6 shows the ECE of pruned Mistral 7B and Llama-3 8B on ARC Easy and TweetEval (the rest of the plots are in Fig. 34 of the appendix). As more attention layers are removed, misalignment between model confidence and accuracy increases for both Mistral and Llama, indicating that **pruning attention layers can worsen the confidence calibration of the model**. We hypothesise this is because layer pruning perturbs internal representations and logits, therefore models' confidence too. Calibration depends on alignment between confidence and accuracy, so even small logits shifts can degrade calibration by affecting confidence but not enough for a prediction flip. In addition, pruning attention layers may make the model over or under confident on individual samples, which further contributes to deterioration in confidence calibration. Qwen is an exception to this: its calibration error improves on sentiment analysis tasks (TweetEval, Rotten Tomatoes, and SST-2). This may be because pruning reduces both the model's confidence and accuracy. Since ECE measures how well confidence matches accuracy, by grouping predictions into confidence bins and comparing the average confidence and accuracy in each bin, lower confidence can cause predictions to be clustered into fewer bins. At the same time, as accuracy slightly drops (Fig. 2), the gap between confidence and accuracy within each bin may also shrink, potentially lowering ECE, despite worse overall accuracy.

Lastly, we examine the relationship between confidence calibration and accuracy. The second row of Fig. 6 shows the relative changes in ECE and accuracy of pruned Mistral 7B and Llama-3 8B on ARC Easy and TweetEval (the rest of the plots are in Fig. 35 in the Appendix). We see that ECE can drop disproportionally

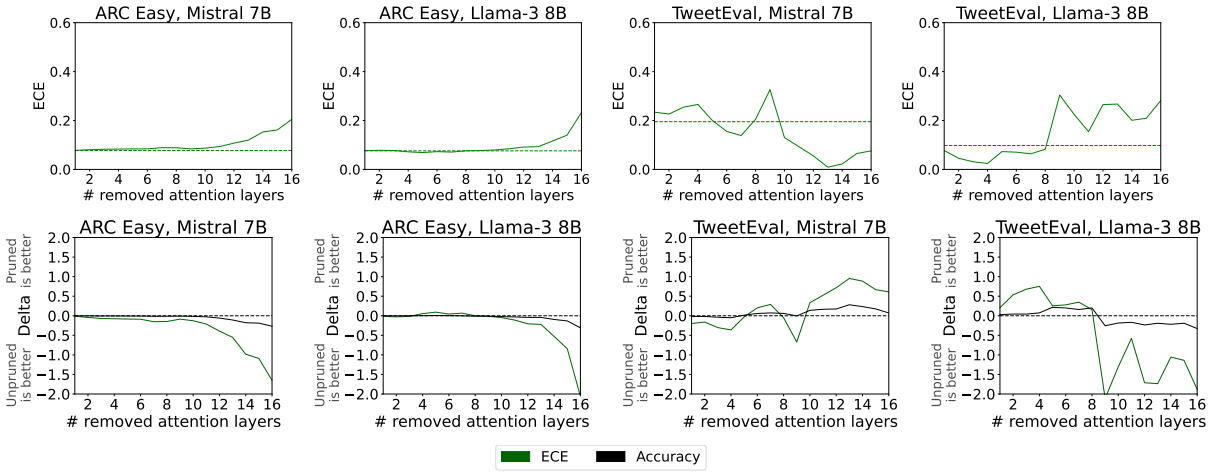

Figure 6: First row: ECE (y axis) for Mistral 7B and Llama-3 8B for different levels of attention layer pruning (x axis). Second row: Relative change in ECE (green line) and accuracy (black line) (y axis) for Mistral 7B and Llama-3 8B for different levels of attention layer pruning (x axis). Accuracy changes are rescaled so that decreases appear lower in the plots and increases higher.

compared to accuracy. In addition, calibration error scores fluctuate unstably on datasets with short labels as attention layers are pruned, while having more stable trends on datasets with longer average label lengths. As this trend is similar to accuracy (see Fig. 3), we show the results in the appendix (see Fig. 8). We believe this trend is partially explained by the fact that for single-token or short-token predictions, model confidence depends heavily on a very small number of tokens, since log-likelihoods are computed over only a limited subset of the sequence. As a result, pruning-induced noise or information loss has a disproportionately large effect, leading to greater fluctuations in predicted confidence for short texts and, consequently, more unstable ECE estimates. As seen for Llama-3 8B on TweetEval in Fig. 6, these fluctuations in calibration error can be notably more pronounced than those observed in accuracy, indicating that **pruning attention layers can lead to unstable fluctuations of model calibration that do not consistently mirror changes in model accuracy**. As previously mentioned, calibration depends on the alignment between confidence and accuracy, and even small logit perturbations can change confidence without affecting predictions, but changing the calibration scores. Additionally, pruning may remove attention heads that are not critical for accuracy but are important for confidence estimation. As a result, we believe that the model can maintain similar accuracy while becoming overconfident or underconfident, leading to unstable and non-monotonic changes in calibration error.

4.4 How does Pruning Attention Layers Affect Plausibility?

The first, second, and third column of Fig. 7 report average F1, precision, and recall respectively for the top-K LIME features (with $K \in \{10, 20, 30, 40, 50\}\%$) identified on Mistral, against human relevance annotations (see Figs. 24-29 for the remaining results). Across measures, plausibility shows a broadly stable behaviour under pruning, likely because pruning mostly preserves features ranking, and plausibility measures compare these rankings directly against human annotations. In contrast, explanation faithfulness varies substantially.

F1 remains comparatively stable, with a small decrease as more layers are pruned. This effect is more pronounced on the top 10% features and is attenuated as K increases, suggesting that pruning primarily perturbs the top ranking attributions while leaving the overall set of important features similar when more features are considered. Precision is mostly invariant across K, aside from isolated cases (e.g., Llama-3 8B on ARC Easy), indicating that the proportion of selected features aligning with human annotations is robust to both pruning and the choice of K. In contrast, recall shows clearly separated curves for different K, increasing with larger feature sets. For most combinations of models and datasets, both precision and recall exhibit a small drop as layers are removed.

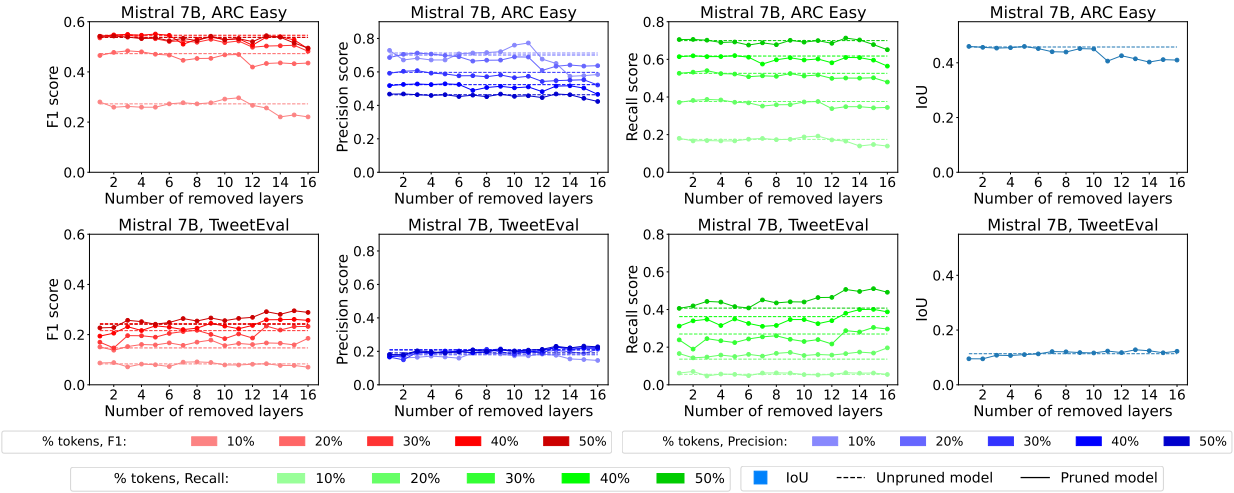

Figure 7: **Columns (left to right):** average F1, Precision, Recall, and IoU between LIME attributions for Mistral 7B and human annotations (y axis), as a function of pruned attention layers (x axis). Dotted lines denote the unpruned model. For F1, Precision, and Recall, colours indicate the proportion of top features considered (K). Rows correspond to datasets: ARC Easy (top) and TweetEval (bottom).

The fourth column of Fig. 7 shows average Intersection-over-Union (similar trends hold for AUPRC and were reported in Appendix for brevity; see Figs. 30-33). Consistent with the F1 analysis, both measures remain broadly stable across pruning levels, with modest drops as more layers are removed. Overall, this shows that explanations' plausibility is resilient to pruning, though still gradually degraded. In contrast, prior results show that faithfulness is more strongly affected, suggesting that while pruning preserves the ranking of salient features, and therefore the agreement with human annotations, it can alter the model's actual reliance on them. As a result, explanations may remain plausible to humans while becoming less faithful to the model's decision process.

4.5 Recommendations for Faithfulness and Calibration Aware Pruning

We present recommendations for designing layer pruning strategies that account for explanation faithfulness and confidence calibration, motivated by our finding that attention layer pruning can degrade both properties independently of accuracy.

Preserving the faithfulness of explanations and confidence calibration ensures that pruned models remain not only accurate but also reliable in their explanations and predictive confidence, increasing their overall trustworthiness. Our results show that both properties can deteriorate without corresponding drops in accuracy, making accuracy alone an insufficient proxy for model quality. We therefore recommend monitoring faithfulness and calibration alongside accuracy throughout the pruning process and using them as stopping criteria. Pruning strategies can be improved by incorporating these properties directly into layer importance scoring, or by adopting iterative approaches that revert pruning steps when they compromise such properties. More broadly, pruning should be treated as a multi-objective optimisation problem, balancing accuracy, explanation faithfulness, and confidence calibration while targeting a desired sparsity level. Finally, post-hoc correction methods, such as lightweight adapters (e.g., LoRA), can be applied after pruning to recover performance while explicitly optimising faithfulness and confidence calibration.

5 Conclusions and Limitations

We studied the impact of attention layer removal on accuracy, explanation faithfulness, plausibility, and confidence calibration for LLMs. We tested five LLMs and eight datasets, and found that LLMs can be substantially pruned, removing up to a third of their attention layers with only modest reductions in accu-

Table 7: Our findings and number of times they hold per model and task.[5] Findings that hold more than 75% of the times are bolded.

Finding	Models					datasets		
	Mistral 7B	Llama-2 7B	Llama-3 8B	Qwen-3 8B	Qwen-3 4B	QA	Sentiment Analysis	NLI
8/8	**8/8**	**8/8**	**8/8**	**8/8**	**15/15**	**15/15**	**10/10**	
The overlap between the most important features between pruned and unpruned LLMs drops as pruning increases (Sec. 4.2, Figs. 10 and 11)	10/16	**16/16**	**12/16**	**15/16**	**15/16**	**24/30**	**24/30**	14/20
Pruning attention layers leads to explanations that are less faithful to the model, hence harder to interpret (Sec. 4.2, Fig. 20 to 23)	**16/16**	11/16	8/16	**16/16**	**16/16**	**30/30**	21/30	**16/20**
Pruning attention layers makes explanation faithfulness unstable in ways not mirrored by changes in accuracy (Sec. 4.2, Fig. 20 to 23)	9/16	10/16	9/16	2/16	5/16	0/30	**24/30**	9/20
Pruning attention layers can worsen the confidence calibration of the model (Sec. 4.3, Fig. 34)	**7/8**	**8/8**	**7/8**	4/8	5/8	**14/15**	10/15	7/10
Pruning attention layers can lead to unstable model calibration in ways not mirrored by changes in accuracy. (Sec. 4.3, Fig. 35)	**6/8**	**6/8**	**6/8**	**6/8**	**6/8**	5/15	**15/15**	**10/10**

racy. For all LLMs but Qwen, the accuracy drop remained relatively small up to 12 removed layers. Despite stable accuracy, we observed that explanation faithfulness degrades with layer pruning. Comprehensiveness and sufficiency scores declined as more layers were removed, indicating that pruned models rely less on the most important input features, yet still consider them sufficient for the prediction. This behaviour may be partly explained by a reduction in the model's average confidence, which affects both comprehensiveness and sufficiency. We also found that pruning can affect explanation faithfulness independently of accuracy, often changing disproportionately and unstably. Our plausibility analysis reveals that, in contrast to faithfulness, which can vary substantially under pruning, plausibility remains comparatively stable, with only mild degradation as layers are removed. We further analysed the alignment between model confidence and accuracy through Expected Calibration Error (ECE), finding that pruning can harm calibration, even when accuracy remains stable. Like explanation faithfulness, the model's error calibration after pruning can change disproportionately and unstably relatively to accuracy, revealing a misalignment between confidence and accuracy that is so far undetected in literature.

Alternative pruning strategies, such as removing MLP layers or applying different pruning criteria like SparseGPT or Wanda, may yield different efficiency-interpretability trade-offs. These methods prune individual weights rather than entire layers and could affect interpretability in unique ways. To our knowledge, no work has compared pruning strategies along this axis, making it a valuable direction for future research.

In addition, further research can explore a broader range of feature attribution methods and faithfulness measures, especially given their low agreement on attribution quality (Barr et al., 2023). Evaluating pruned models across diverse downstream tasks and further exploring plausibility of pruned models using annotated datasets for plausibility, could deepen our understanding of trade-offs between efficiency, faithfulness, plausibility, and calibration. Furthermore, prompt design remains an open question. Our experiments use a single zero-shot prompt, leaving it unclear how sensitive the observed effects are to prompt variations. Investigating whether specific prompting techniques can mitigate degradation in explanation faithfulness and calibration could offer valuable insights, though such analysis would be computationally intensive.

This study investigated the effects of attention layer removal pruning. While this approach provides valuable insights, we acknowledge that it represents only one strategy within a broader class of pruning techniques. Future work should explore the effect of additional layer removal strategies on LLMs and a wider range of pruning strategies, for instance, common pruning methods such as SparseGPT (Frantar & Alistarh, 2023) and Wanda (Sun et al., 2024). Additionally, evaluating pruned models using a broader set of feature attribution methods would further strengthen the generalizability of the conclusions to explainers beyond surrogate-based methods. This work focused on pruned LLMs and, therefore, cannot be applied to black-box models, as it requires access to model weights. Our study is limited to decoder-based LLMs and trends may vary on other architectures. Additionally, our setup required up to 40GB of GPU memory, which may limit

[5]We treat BoolQ as an NLI task since it uses text pairs and a prompt structure similar to NLI tasks

the reproducibility of similar studies on hardware with lower memory availability. Finally, due to the high computational cost of faithfulness evaluation, we limited our analysis to 200 randomly sampled instances per dataset. Even under this constraint, our experiments exceeded 6000 GPU hours.

Broader Impact and Ethics Statement

As LLMs grow more complex, layer pruning is an effective and simple strategy to democratise access to state-of-the-art models. While layer pruning can produce efficient models with minimal accuracy loss, our findings show that it may come at the cost of explanation faithfulness and confidence calibration, two critical properties for trustworthy AI. These trade-offs should be considered when deploying pruned models in the real-world, especially in high-stakes settings where explainability may be as important as accuracy. For example, in legal summarisation, feature attributions can help highlight which parts of a document contributed most to the summary, supporting transparency and trust. However, a pruned LLM may still produce a fluent summary while attributions point towards irrelevant or misleading parts of the input. This faithfulness degradation can mislead legal professionals and ultimately undermine the reliability of the summarisation system. In healthcare, poor calibration may cause models to appear overconfident. This could reduce trust if clinicians notice the misalignment, or lead to relying too much on the LLMs, potentially resulting in unsafe clinical decisions once the model produces a wrong diagnosis. These examples highlight the societal risks of evaluating pruned models solely based on accuracy. Trustworthiness must be assessed holistically, considering not just accuracy but also how models reason and how well their confidence aligns with their actual correctness.

While our findings expose certain limitations of pruning LLMs, we emphasise that pruning remains highly relevant, particularly for low-resource environments and for enabling more sustainable deployment of LLMs. Our goal is not to discourage their use, but rather to encourage their responsible and informed application.

To the best of our knowledge, we have cited all relevant prior work and adhered to the JMLR ethics guidelines. We recognise that studies involving large-scale model evaluations can be computationally intensive, potentially limiting reproducibility. To mitigate this and promote transparency, we share our code and relevant implementation details to facilitate replication of our results.

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Yang Zhang, Yanfei Dong, and Kenji Kawaguchi. Investigating layer importance in large language models. In Yonatan Belinkov, Najoung Kim, Jaap Jumelet, Hosein Mohebbi, Aaron Mueller, and Hanjie Chen (eds.), *Proceedings of the 7th BlackboxNLP Workshop: Analyzing and Interpreting Neural Networks for NLP*, pp. 469–479, Miami, Florida, US, November 2024b. Association for Computational Linguistics. doi: 10.18653/v1/2024.blackboxnlp-1.29. URL https://aclanthology.org/2024.blackboxnlp-1.29/.

Yang Zhang, Yawei Li, Xinpeng Wang, Qianli Shen, Barbara Plank, Bernd Bischl, Mina Rezaei, and Kenji Kawaguchi. Finercut: Finer-grained interpretable layer pruning for large language models, 2024c. URL https://arxiv.org/abs/2405.18218.

Yingtao Zhang, Haoli Bai, Haokun Lin, Jialin Zhao, Lu Hou, and Carlo Vittorio Cannistraci. Plug-and-play: An efficient post-training pruning method for large language models. In *The Twelfth International Conference on Learning Representations*, 2024d. URL https://openreview.net/forum?id=Tr0lPx9woF.

A Methodology

We provide additional details on the datasets, models, and attribution methods used in our study.

A.1 Datasets

We evaluate our models on eight NLP datasets:

ARC Easy and ARC Challenge. ARC Easy and ARC Challenge (Clark et al., 2018) are multiple-choice science question datasets, each with four answer options per question. Both are available under a CC BY-SA 4.0 license.

OpenBookQA OpenBookQA (Mihaylov et al., 2018) is a multiple-choice question answering dataset that requires multi-step reasoning and common knowledge. Each question has four answer choices. The dataset is available under Apache License 2.0.

BoolQ. BoolQ (Clark et al., 2019) consists of yes/no questions paired with contextual passages. It covers a wide range of topics and is available under a CC BY-SA 3.0 license.

RTE. RTE (Wang et al., 2018) is a natural language inference dataset derived from RTE1-RTE3, and RTE5 (Dagan et al., 2006; Haim et al., 2006; Giampiccolo et al., 2007; Bentivogli et al., 2009). Each instance is given by a pair of sentences and the task is to predict entailment. Each instance consists of a sentence pair, and the task is to predict entailment. While the GLUE benchmark does not specify a license for RTE, the RTE1-RTE3, and RTE5 datasets were made available for non-commercial research use. To the best of our knowledge, the original licenses are not publicly accessible.

TweetEval. TweetEval (Barbieri et al., 2020), (sentiment partition) (Rosenthal et al., 2017) is a Twitter-based sentiment classification dataset with tweets labelled as positive, negative, or neutral. It is available under a CC BY-SA 3.0 Unported license.

Rotten Tomatoes. Rotten Tomatoes (Pang & Lee, 2005) is a movie review sentiment dataset containing short reviews labelled as positive or negative. The dataset is distributed under an Apache License 2.0 through public dataset wrappers, though, to the best of our knowledge, the original data does not specify a license.

SST-2. SST-2 (Socher et al., 2013) is a binary sentiment classification dataset derived from the Stanford Sentiment Treebank. Similar to Rotten Tomatoes, the dataset is distributed under an Apache License 2.0 through public dataset wrappers, though, to the best of our knowledge, the original data does not specify a license.

A.2 Prompt templates

We report the prompt templates used in our study:

ARC Easy and ARC Challenge. We used the default prompt template provided by LM Evaluation Harness (Gao et al., 2024) to prompt the LLMs on this task. Precisely, the template is:

```
Question: [question]
Answer:
```

OpenBookQA. We used the default prompt template provided by LM Evaluation Harness (Gao et al., 2024) to prompt the LLMs on this task. Precisely, the template is:

```
[question]
```

BoolQ. We used the default prompt template provided by LM Evaluation Harness (Gao et al., 2024) to prompt the LLMs on this task. Precisely, the template is:

```
[passage]
Question: [question]?
Answer:
```

RTE. We used the default prompt template provided by LM Evaluation Harness (Gao et al., 2024) to prompt the LLMs on this task. Precisely, the template is:

```
[sentence1]
Question: [sentence2] True or False?
Answer:
```

TweetEval. We used the second prompt template provided by promptsource (Bach et al., 2022) for the sentiment set of TweetEval to prompt the LLMs on this task. Precisely, the template is:

```
What is the sentiment of the tweet?

[tweet]

Possible choices: positive, neutral, or negative
Answer:
```

Rotten tomatoes. We used the third prompt template provided by promptsource (Bach et al., 2022) to prompt the LLMs on this task. Precisely, the template is:

```
[review]
Is this review positive or negative?
Answer:
```

SST-2. We used the default prompt template provided by LM Evaluation Harness (Gao et al., 2024) to prompt the LLMs on this task. Precisely, the template is:

```
[sentence]
Question: Is this sentence positive or negative?
Answer:
```

A.3 Language Models

We use five decoder-based LLMs in our experiments:

Mistral 7B. Mistral 7B (Jiang et al., 2023), released under the Apache License 2.0

Llama-2 7B. Llama-2 7B (Touvron et al., 2023), released under the Llama 2 community license.

Llama-3 8B. Llama-3 8B (Team, 2024), released under the Llama 3 community license.

Qwen-3 8B. Qwen-3 8B (Yang et al., 2025), released under the Apache License 2.0

Qwen-3 4B. Qwen-3 4B (Yang et al., 2025), released under the Apache License 2.0

A.4 Accuracy, Faithfulness, and Confidence Calibration Fluctuations Across Pruning Thresholds

We compute accuracy, ECE, sufficiency, and comprehensiveness fluctuations (see Figs. 8 and 9). For faithfulness measures, scores are averaged over three random seeds used for attributions. We evaluate fluctuations per model by tracking score trends across pruning levels, from the unpruned model up to removing 16 attention layers. We first determine the initial trend (increasing or decreasing) as we prune the first layer; a fluctuation is counted when the score changes by at least 5% in the opposite direction of the current trend, at which point the trend is updated, and tracking continues. We report the average number of fluctuations across models (y-axis). To account for tokenisation differences, the x-axis shows the average number of tokens per label across models on the dataset.

In summary, this analysis shows how stable model performance and faithfulness measures are under progressive pruning, by quantifying how often their trends change and relating this instability to the number of tokens used to represent labels.

A.5 Plausibility Study

We include here the instructions that were given to the annotators.

```
Instructions
Thank you for participating in this study! Please read the instructions carefully.
Warning: this study may contain offensive words which may be upsetting.
You will be given 64 sentence-labels pairs.
For each sentence, select and bold the word(s) that make you associate the
sentence with a specific label.

Example:

Sentence:
Which of these is a place where a human might live?

Labels:
igloo, cloud, mars, the moon

Annotation:
Which of these is a place where a human might live?
```

A.6 Summary of Hyperparameters and Experimental Settings

- **Prompting.** All models were evaluated in a zero-shot setting using greedy decoding. We used the standard LM-eval-harness (Gao et al., 2024) prompt templates for each dataset, with the exception of TweetEval and Rotten Tomatoes, for which we selected prompt templates from promptsource (Bach et al., 2022).

- **Layer Pruning.** We followed He et al. (2026) and pruned attention layers iteratively based on their block influence scores (Men et al., 2024), computed as the cosine similarity between each layer's input and output representations. Scores were estimated using **8 sequences of 2048 tokens** sampled from the C4 dataset.

- **Feature attribution.** We compute feature attributions using LIME (Ribeiro et al., 2016) and Kernel SHAP (Lundberg & Lee, 2017). Following Edin et al. (2024), we set the number of samples used to train the surrogate models to three times the number of input features.
- **Faithfulness Evaluation.** Due to computational constraints, we evaluated explanation faithfulness on **200 randomly sampled instances per dataset**. Feature attributions were computed using **three random seeds**. We used 10%, 20%, 30%, 40%, and 50% as thresholds for *comprehensiveness* and sufficiency.
- **Confidence calibration.** We computed Expected Calibration Error (ECE) using **10 equidistant bins**, following Naeini et al. (2015).
- **Statistical tests** We use McNemar's test for accuracy and the Wilcoxon test for faithfulness measures, as the scores are not normally distributed.
- **Hardware Requirements.** Our experiments required up to **40 GB of GPU memory**, and the full evaluation, including faithfulness, exceeded **6000 GPU hours** utilising a combination of NVIDIA L40S, A40 and A100 GPUs.

B Results

We report here the complete set of individual results for all analyses presented in the paper.

Figs. 8 and 9 show the number of fluctuations observed in accuracy and ECE, and in comprehensiveness and sufficiency, respectively.

Figs. 10 and 11 present the overlap among the top 5, 10, and 20 features identified by LIME and Kernel SHAP, respectively, for pruned and unpruned models, as a function of the number of pruned attention layers.

Figs. 12-15 report comprehensiveness, sufficiency, and accuracy for pruned models across all datasets, using both LIME and Kernel SHAP, at varying levels of attention layer removal.

In Fig. 5, we found that pruning attention layers can affect both their comprehensiveness and sufficiency. To determine whether this trend is due to specific bins, we plot sufficiency and comprehensiveness for each bin, i.e., the bins containing 10%, 20%, 30%, 40%, and 50% of the tokens. Figs. 16, 17, 18, and 19 demonstrate that the individual bins used to compute sufficiency and comprehensiveness exhibit the same behaviour as the aggregated measures. Therefore, no single bin disproportionately affects the aggregated measurements of sufficiency and comprehensiveness.

Figs. 20-23 illustrate the relative reductions in comprehensiveness, sufficiency, and accuracy between pruned and unpruned models across different levels of attention layer removal.

Figs. 24-29 report average F1, precision, and recall for the top-K features (with $K \in 10, 20, 30, 40, 50\%$) against human relevance annotations.

Figs. 30-33 further report average Intersection-over-Union (IoU) and Area Under the Precision-Recall Curve (AUPRC).

Fig. 34 presents the Expected Calibration Error (ECE) for all models at varying degrees of attention layer removal. Fig. 35 shows the corresponding relative reductions in ECE and accuracy.

Finally, Tabs. 8-47 provide the complete individual results for accuracy, ECE, and the comprehensiveness and sufficiency scores computed using LIME and Kernel SHAP across all models and datasets.

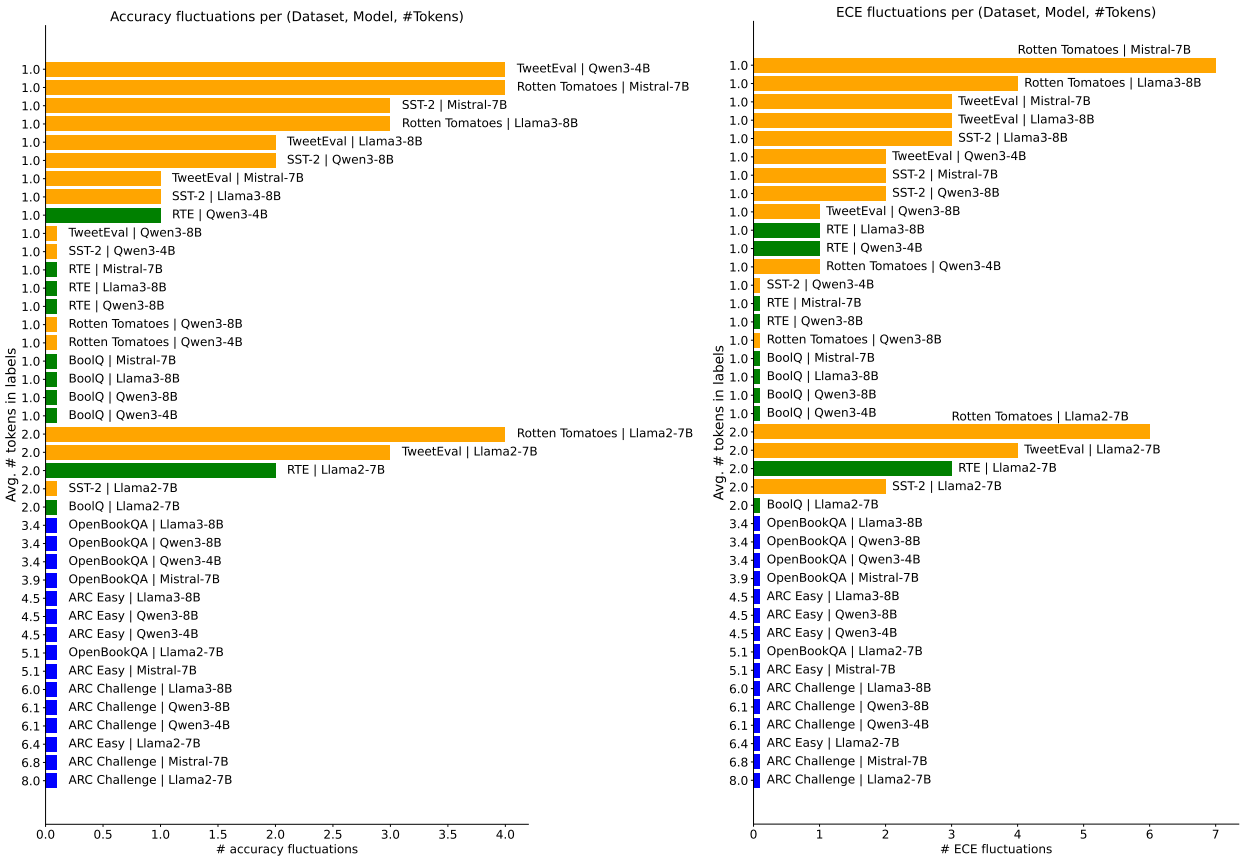

Figure 8: Number of fluctuations (x-axis) in accuracy (first barplot) and ECE (second barplot) for combinations of datasets and models with different average number of label tokens (y-axis).

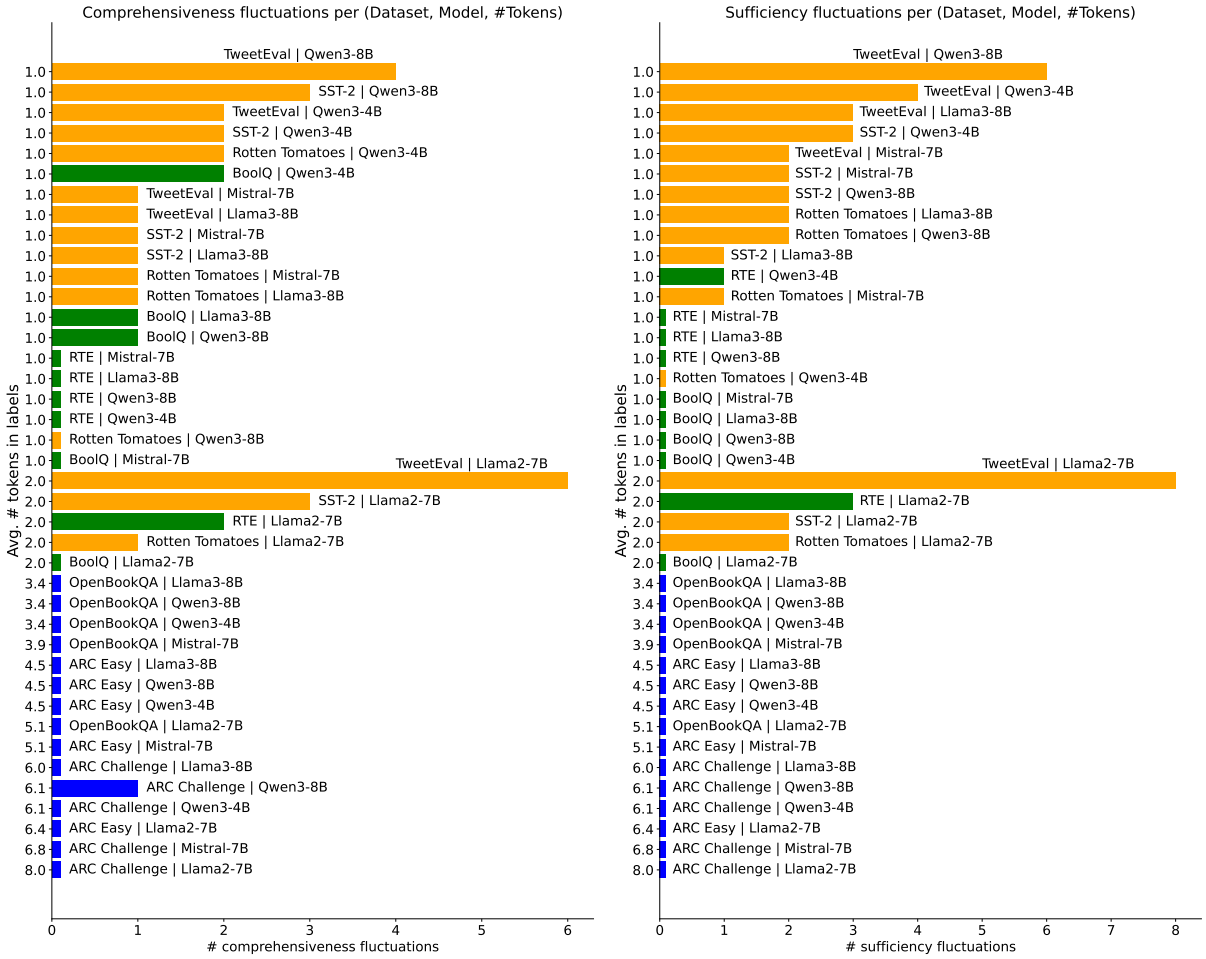

Figure 9: Number of fluctuations (x-axis) in comprehensiveness (first barplot) and sufficiency (second barplot) for combinations of datasets and models with different average number of label tokens (y-axis).

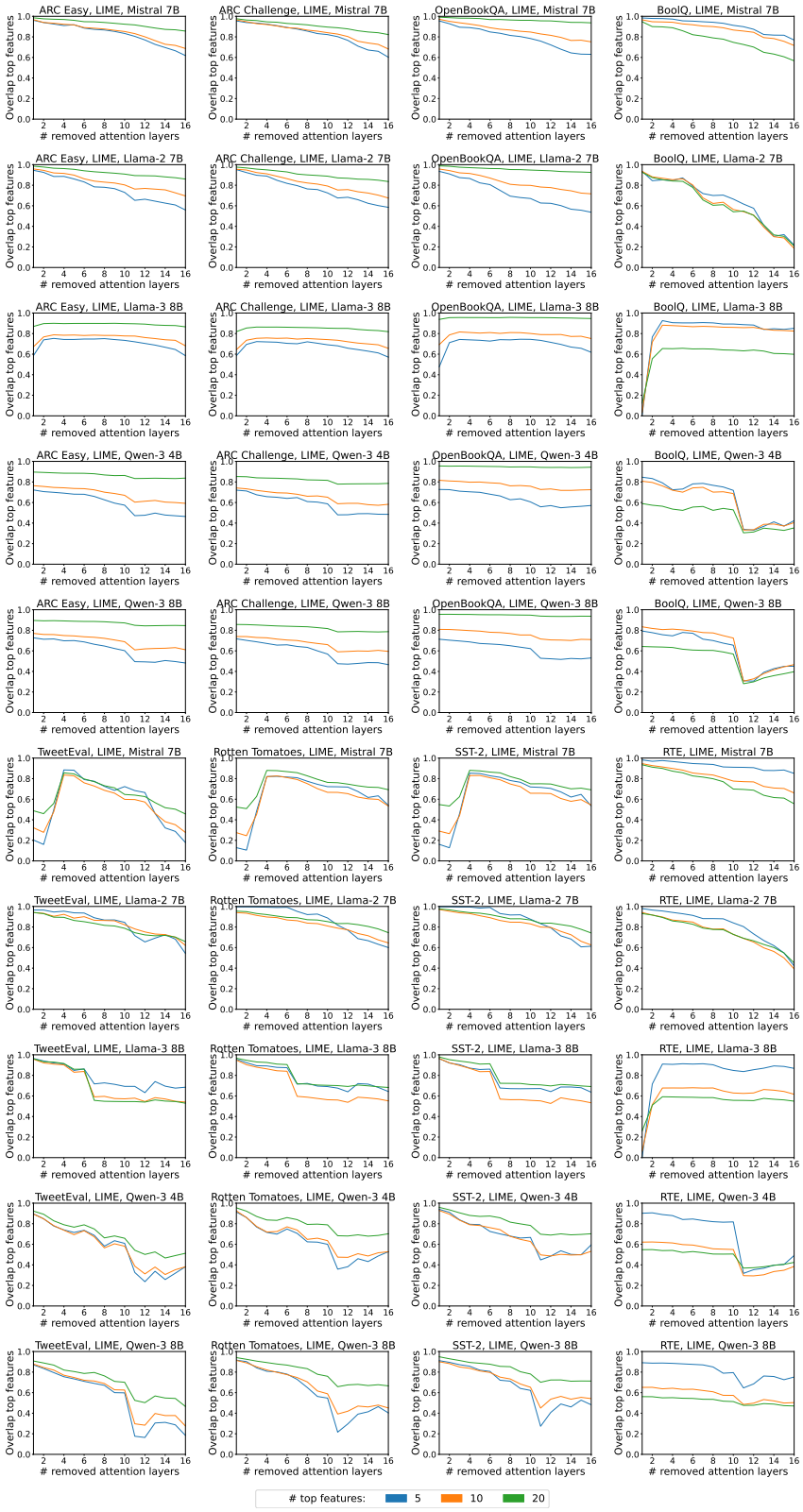

Figure 10: Overlap between the top 5, 10, and 20 features identified by LIME (y-axis) for pruned and unpruned models, as a function of the number of pruned attention layers (x-axis).

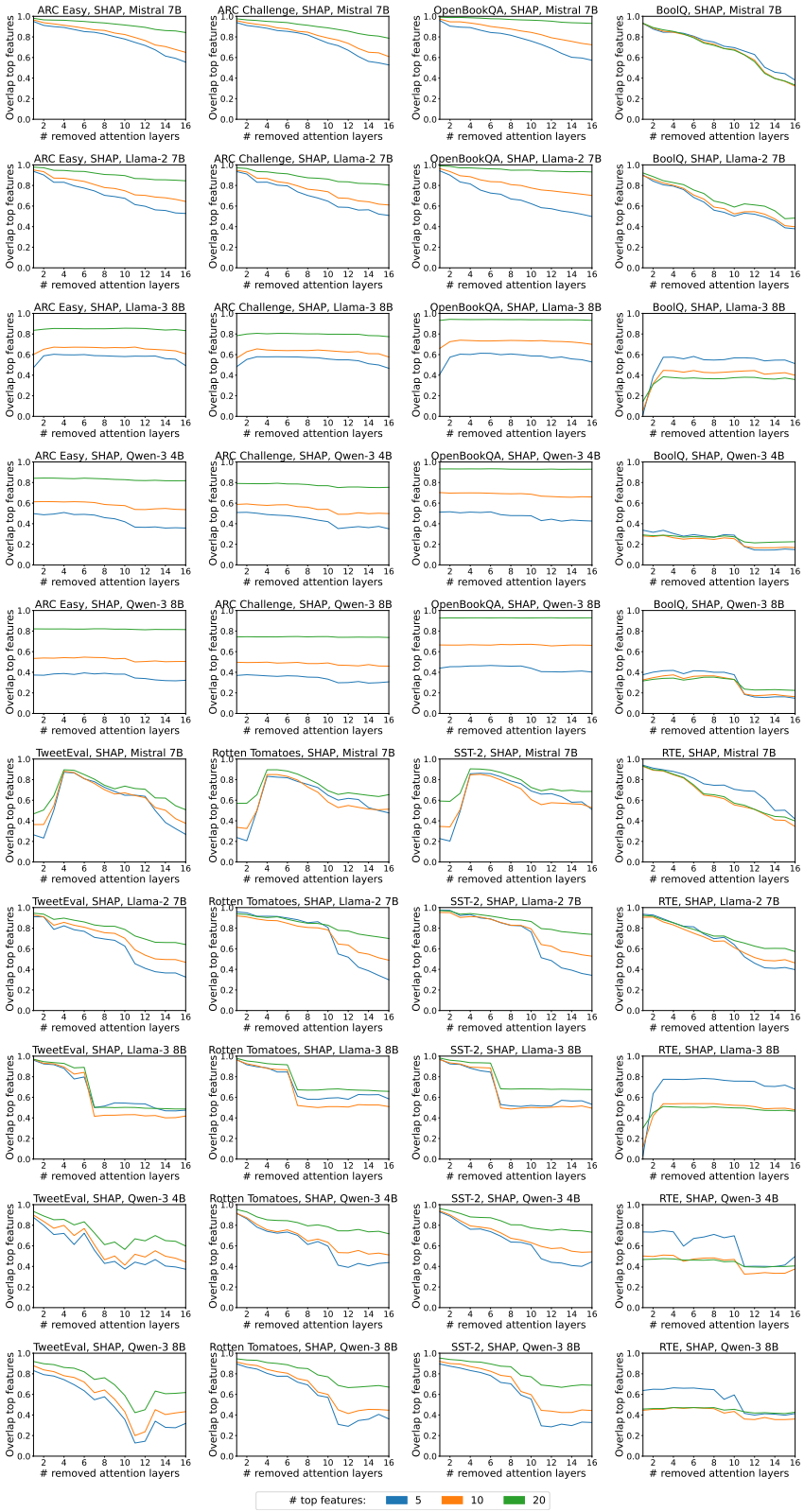

Figure 11: Overlap between the top 5, 10, and 20 features identified by Kernel SHAP (y-axis) for pruned and unpruned models, as a function of the number of pruned attention layers (x-axis).

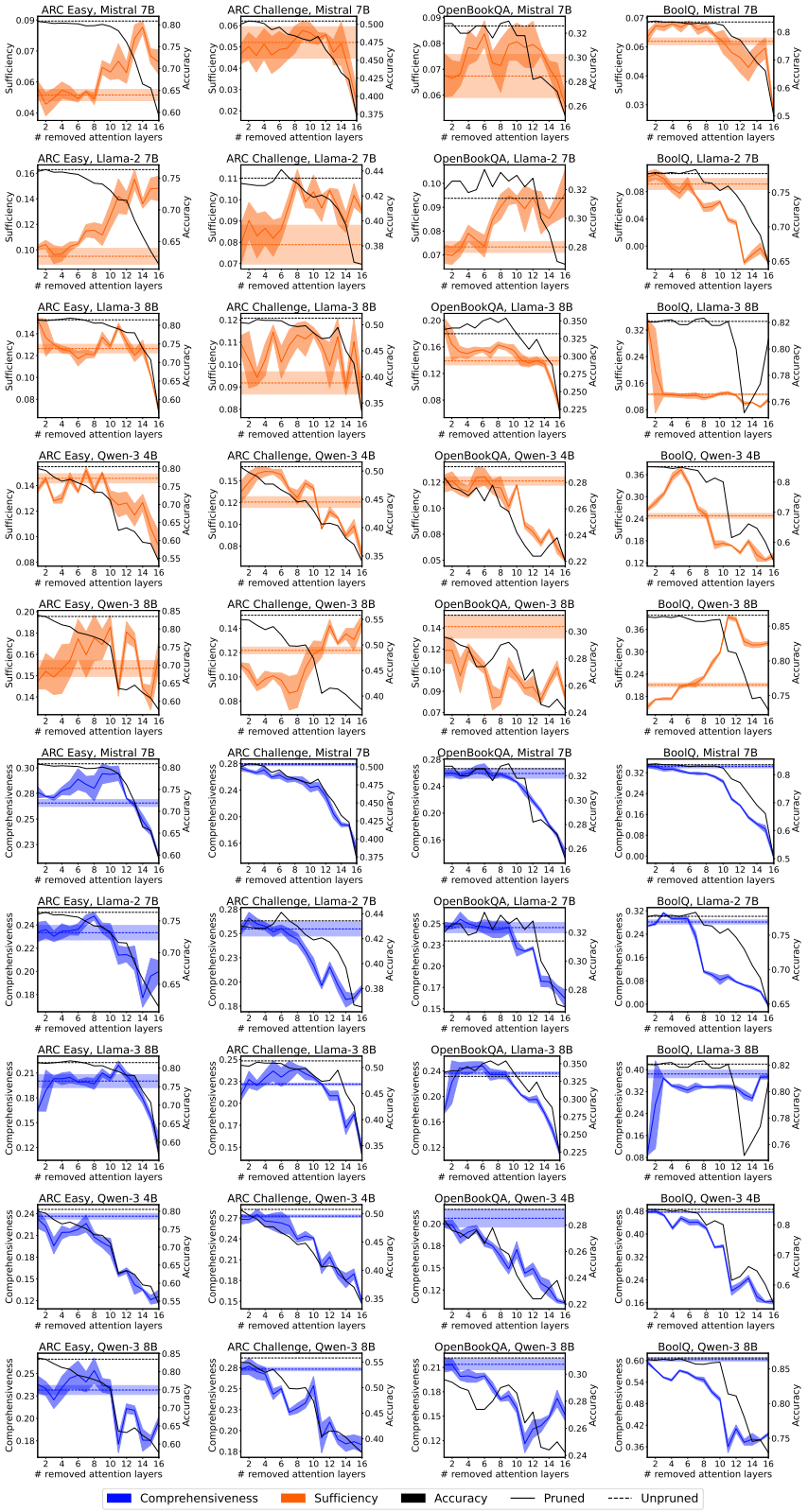

Figure 12: Comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on QA tasks, using LIME, at varying amounts of removed attention layers (x axis).

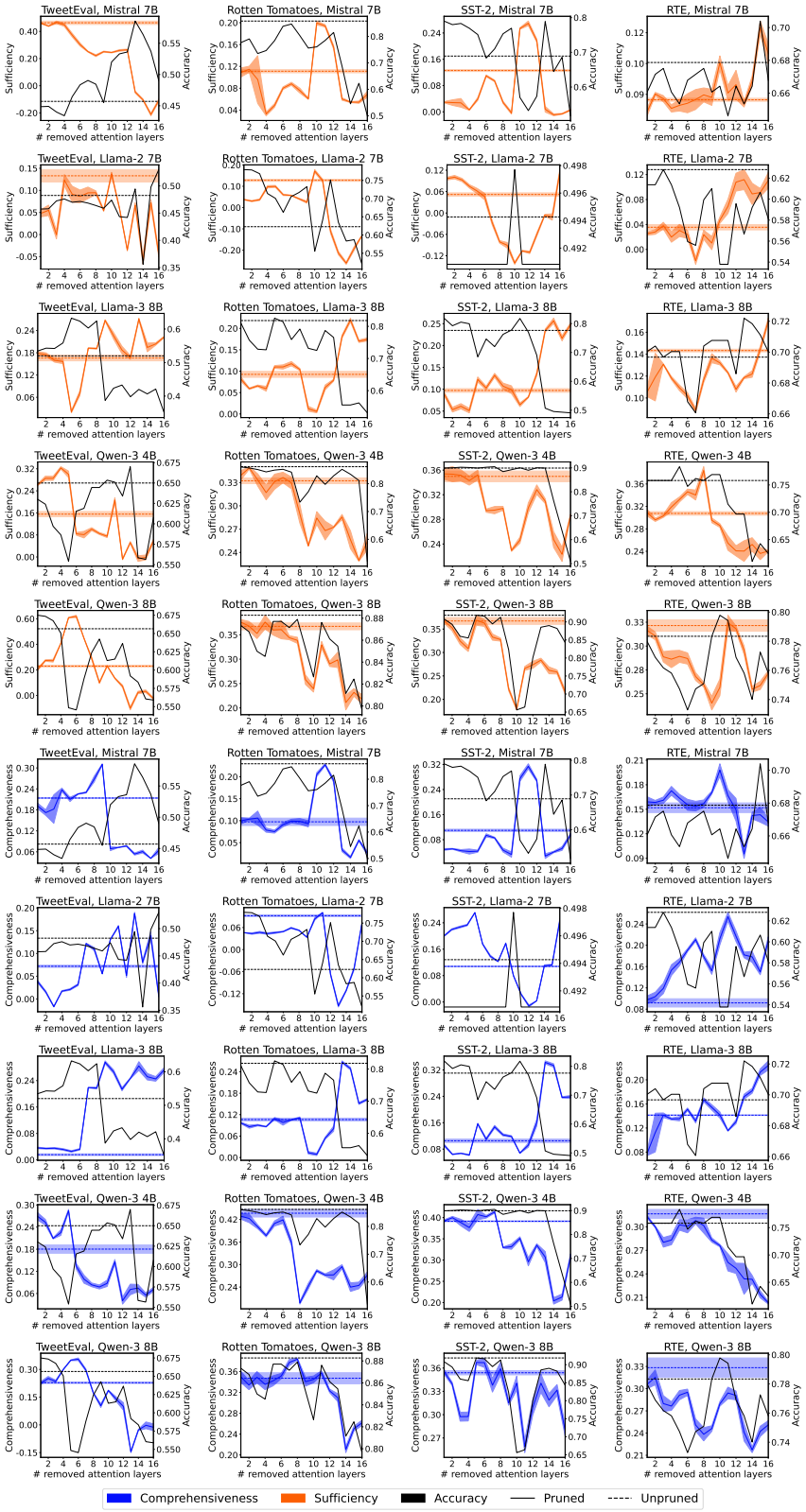

Figure 13: Comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on sentiment analysis tasks and RTE, using LIME, at varying amounts of removed attention layers (x axis).

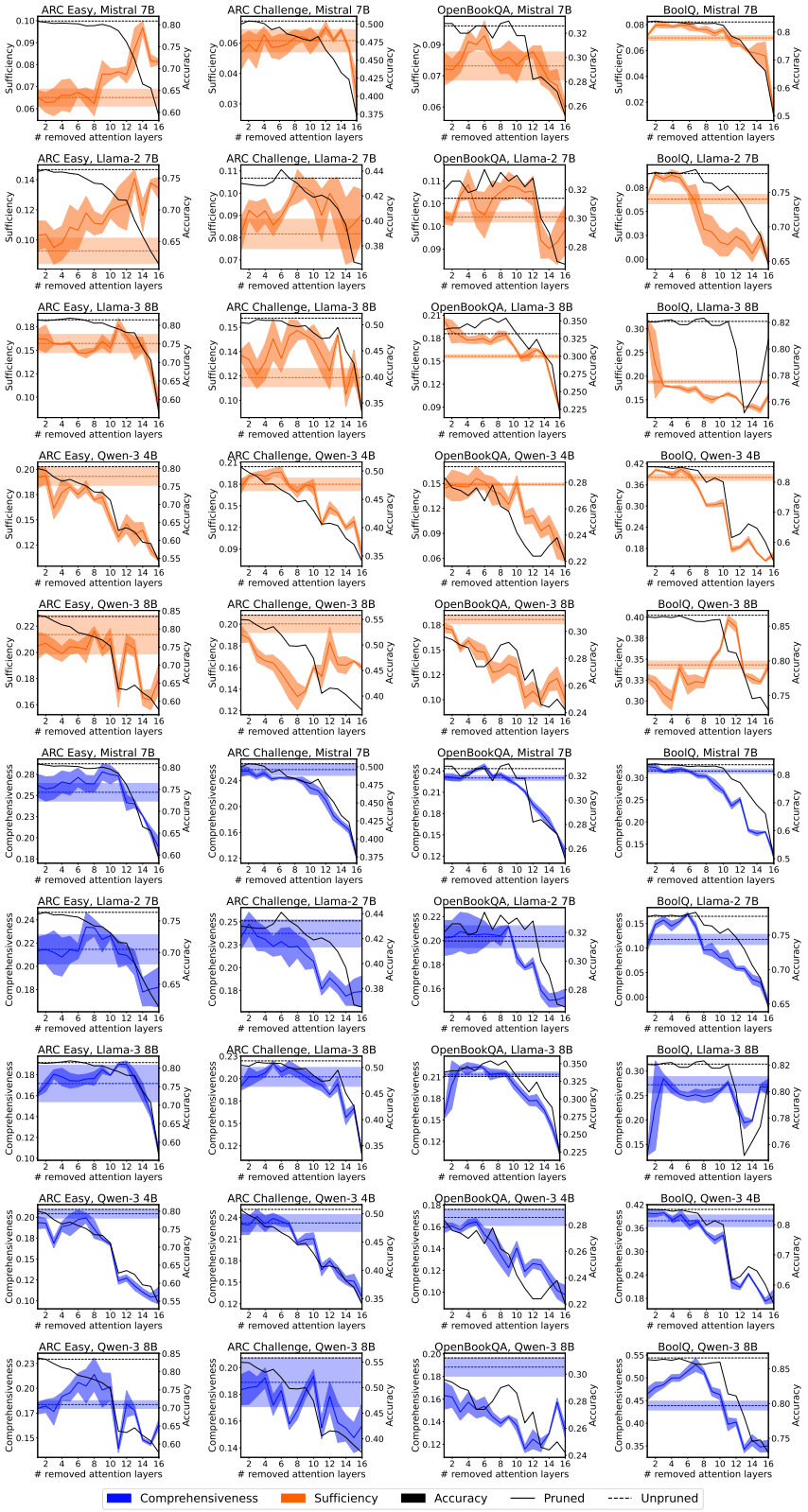

Figure 14: Comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on QA tasks, using Kernel SHAP, at varying amounts of removed attention layers (x axis).

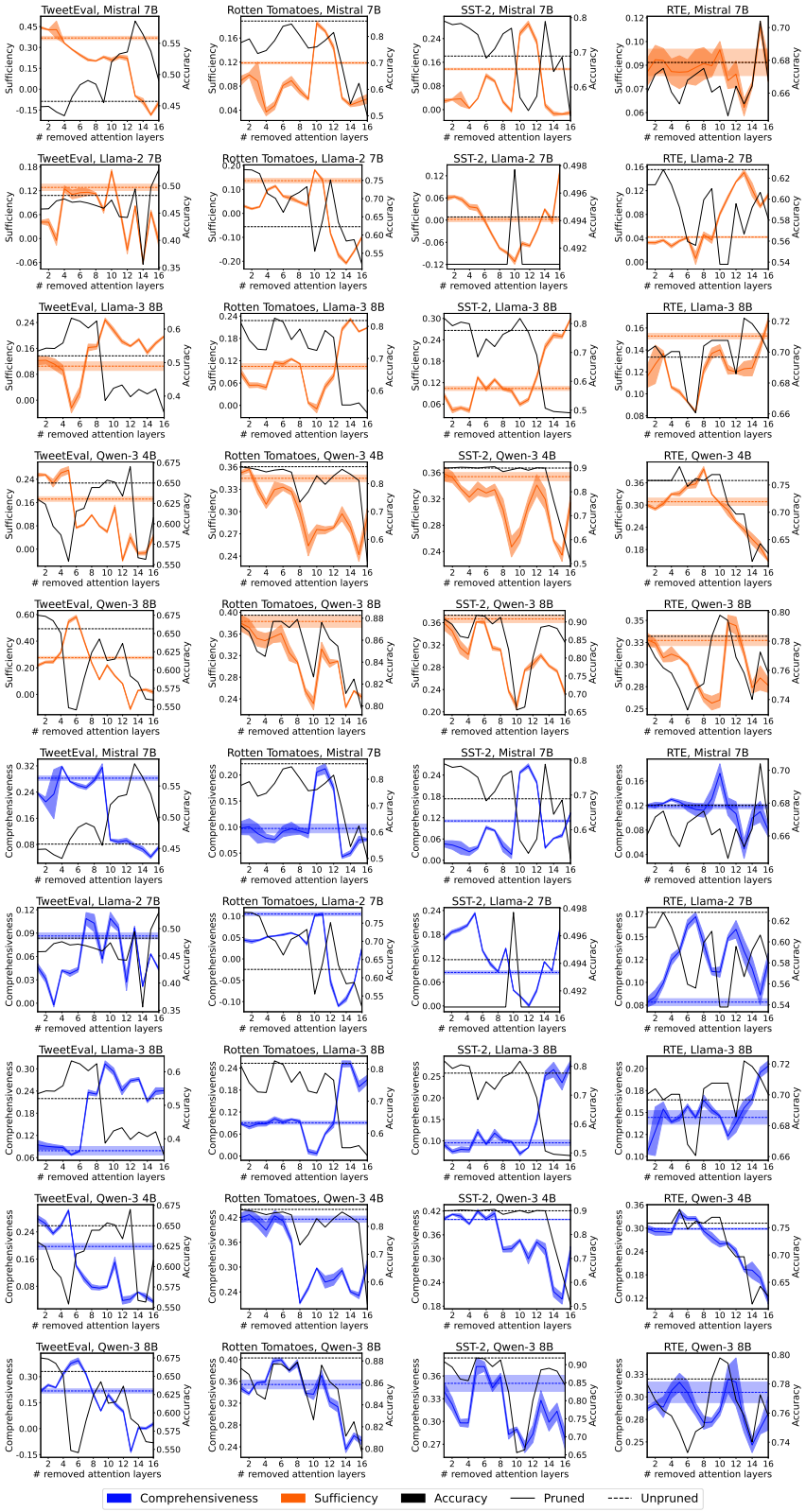

Figure 15: Comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on sentiment analysis tasks and RTE, using Kernel SHAP, at varying amounts of removed attention layers (x axis).

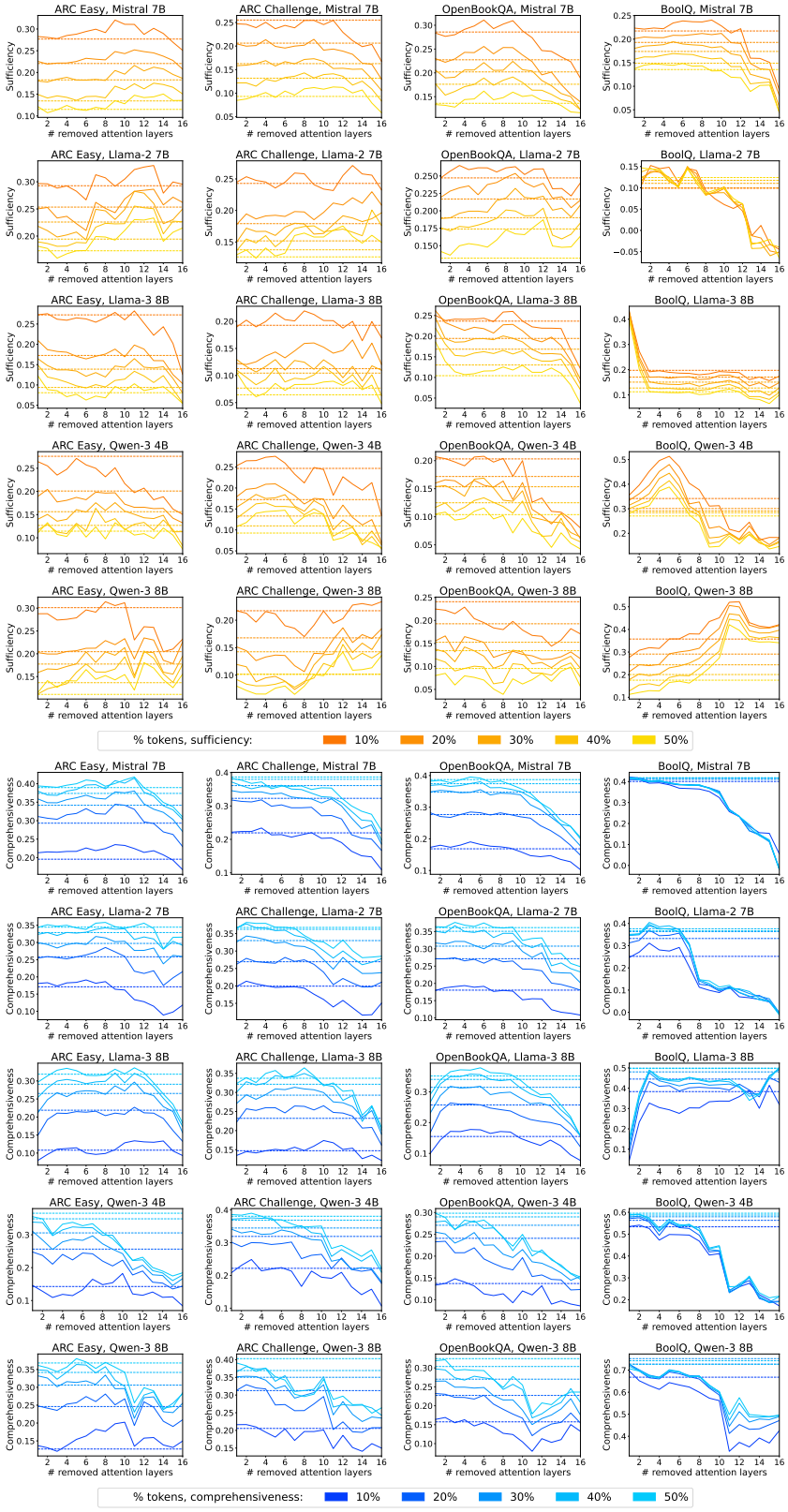

Figure 16: Partial comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on QA tasks, using LIME, at varying amounts of removed attention layers (x axis).

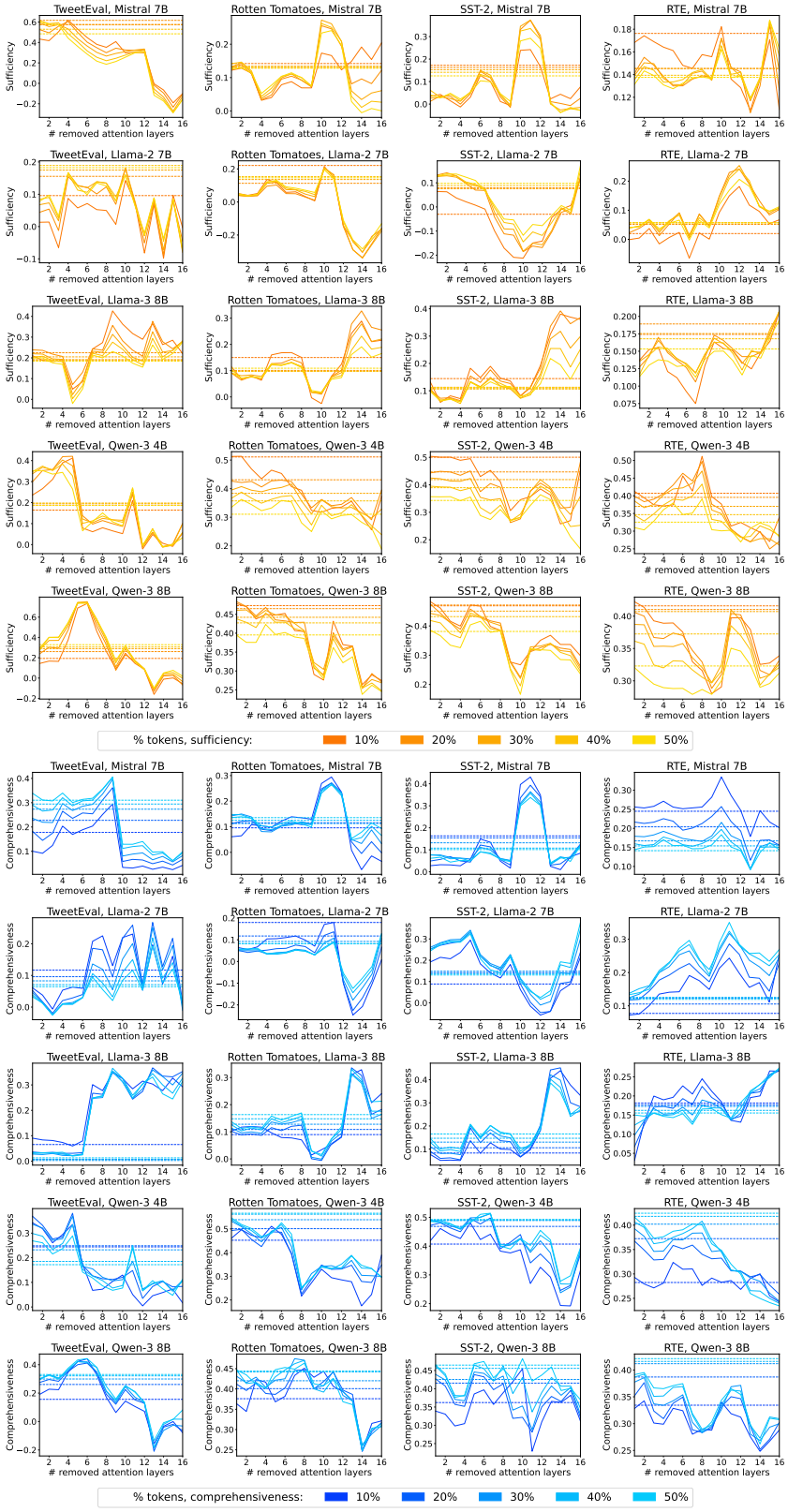

Figure 17: Partial comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on sentiment analysis and RTE tasks, using LIME, at varying amounts of removed attention layers (x axis).

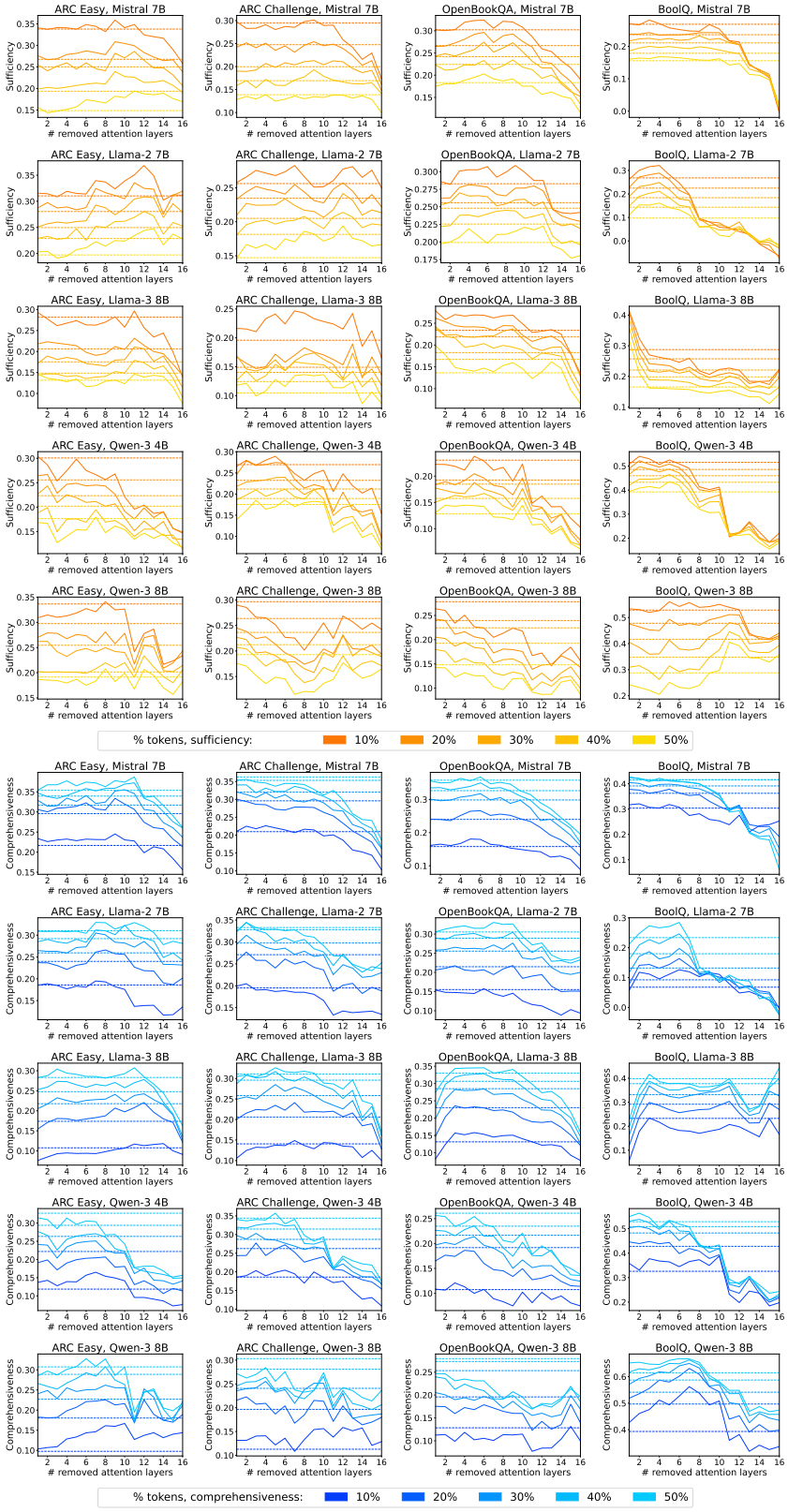

Figure 18: Partial comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on QA tasks, using Kernel SHAP, at varying amounts of removed attention layers (x axis).

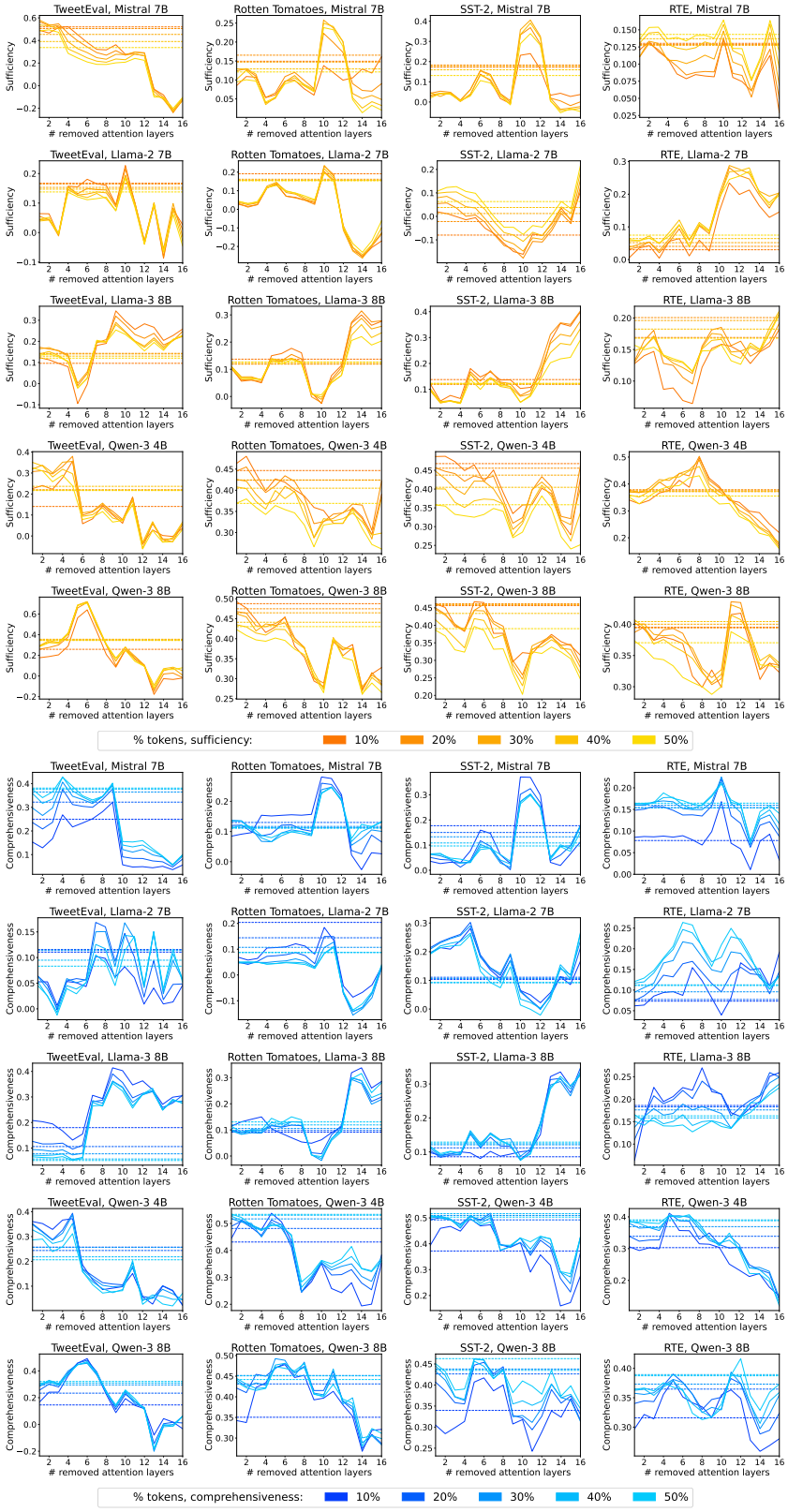

Figure 19: Partial comprehensiveness (↑), sufficiency (↓), and accuracy (↑) of models (y axis) on sentiment analysis and RTE tasks, using Kernel SHAP, at varying amounts of removed attention layers (x axis).

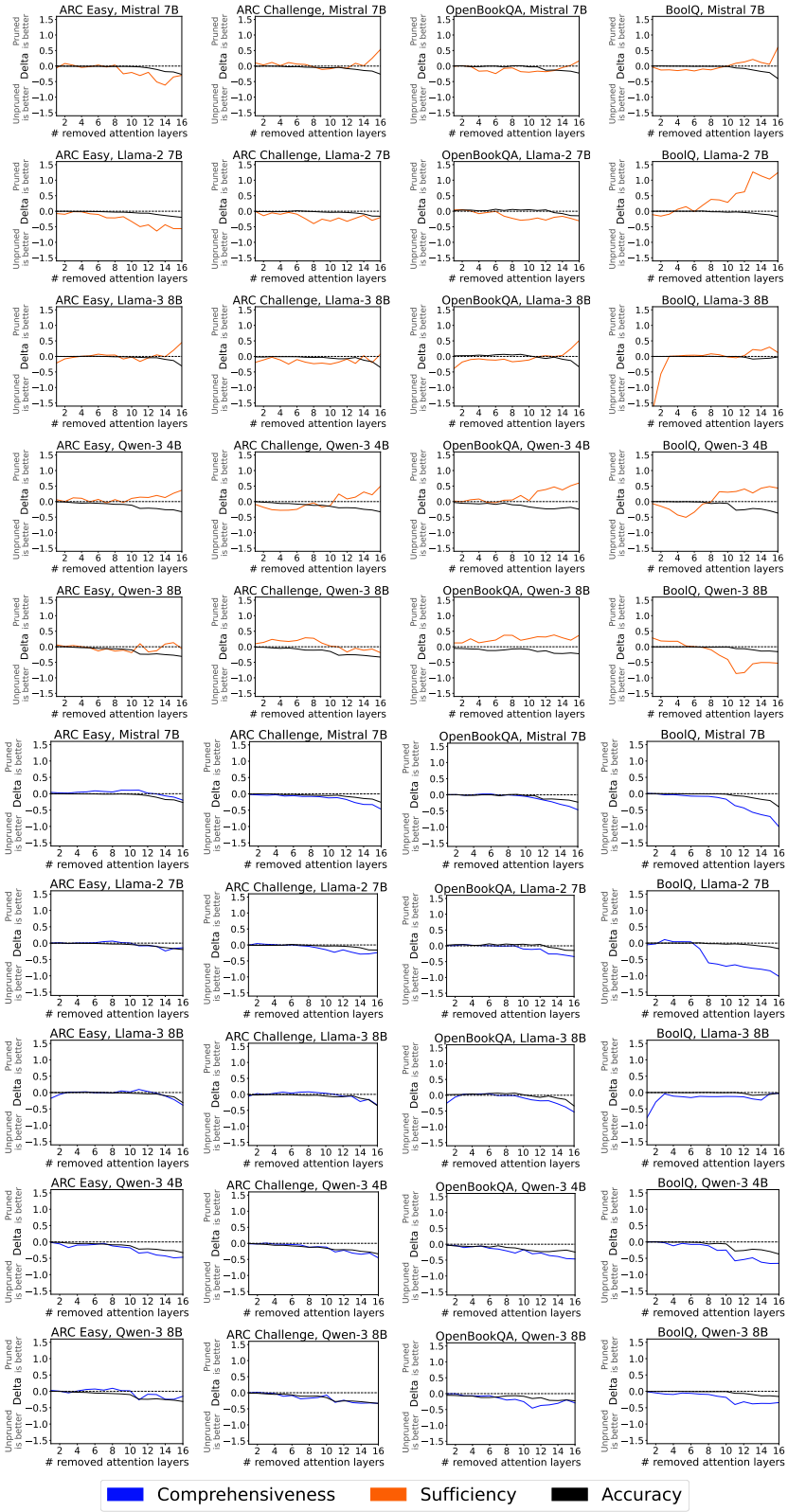

Figure 20: Relative reduction in comprehensiveness and sufficiency using LIME, and accuracy (y axis) between pruned and unpruned models across varying levels of attention layer removal. Accuracy and comprehensiveness reductions are negated, so that negative effects appear on the lower side of the plot.

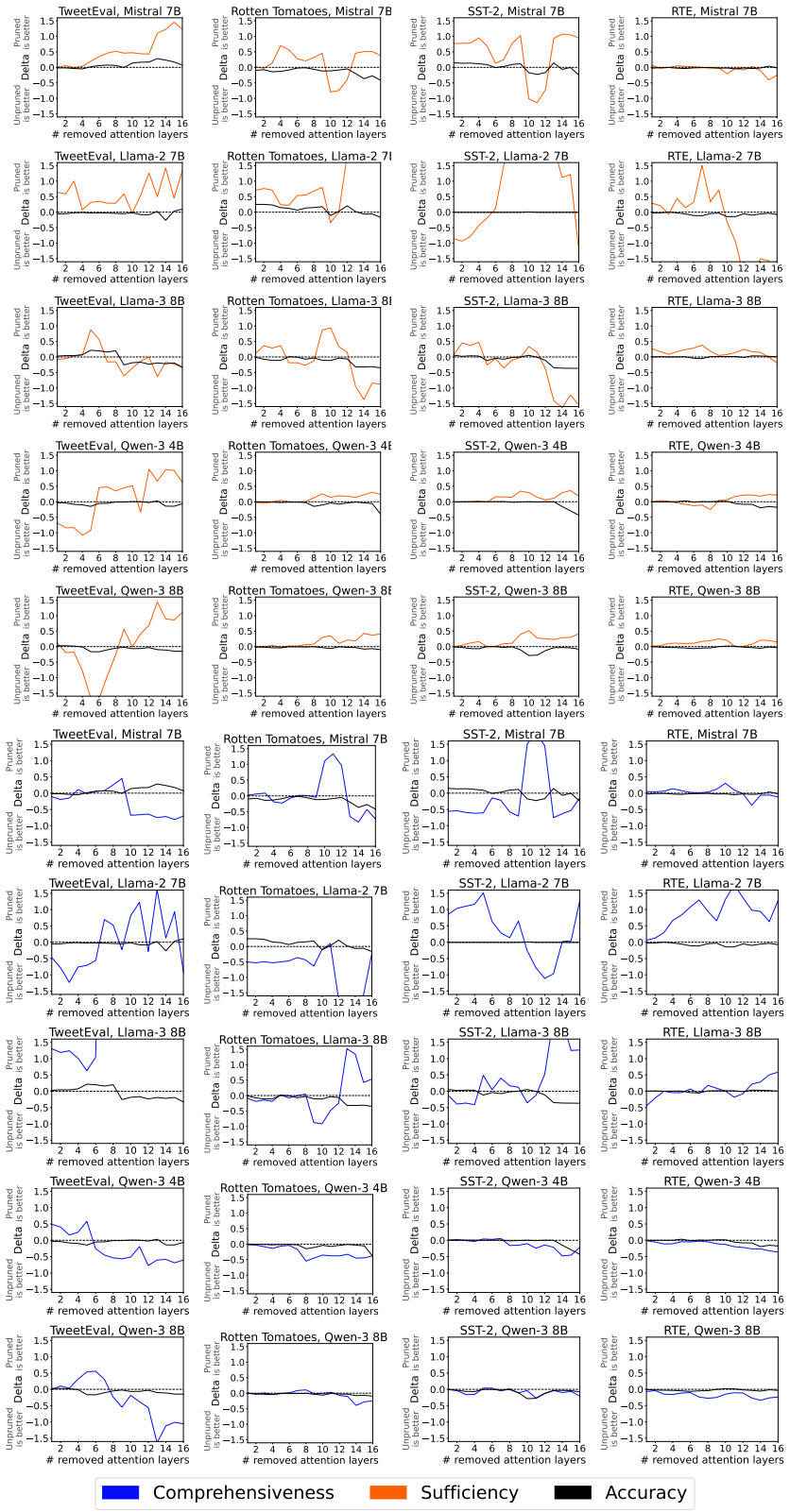

Figure 21: Relative reduction in comprehensiveness and sufficiency using LIME, and accuracy (y axis) between pruned and unpruned models across varying levels of attention layer removal. Accuracy and comprehensiveness reductions are negated, so that negative effects appear on the lower side of the plot.

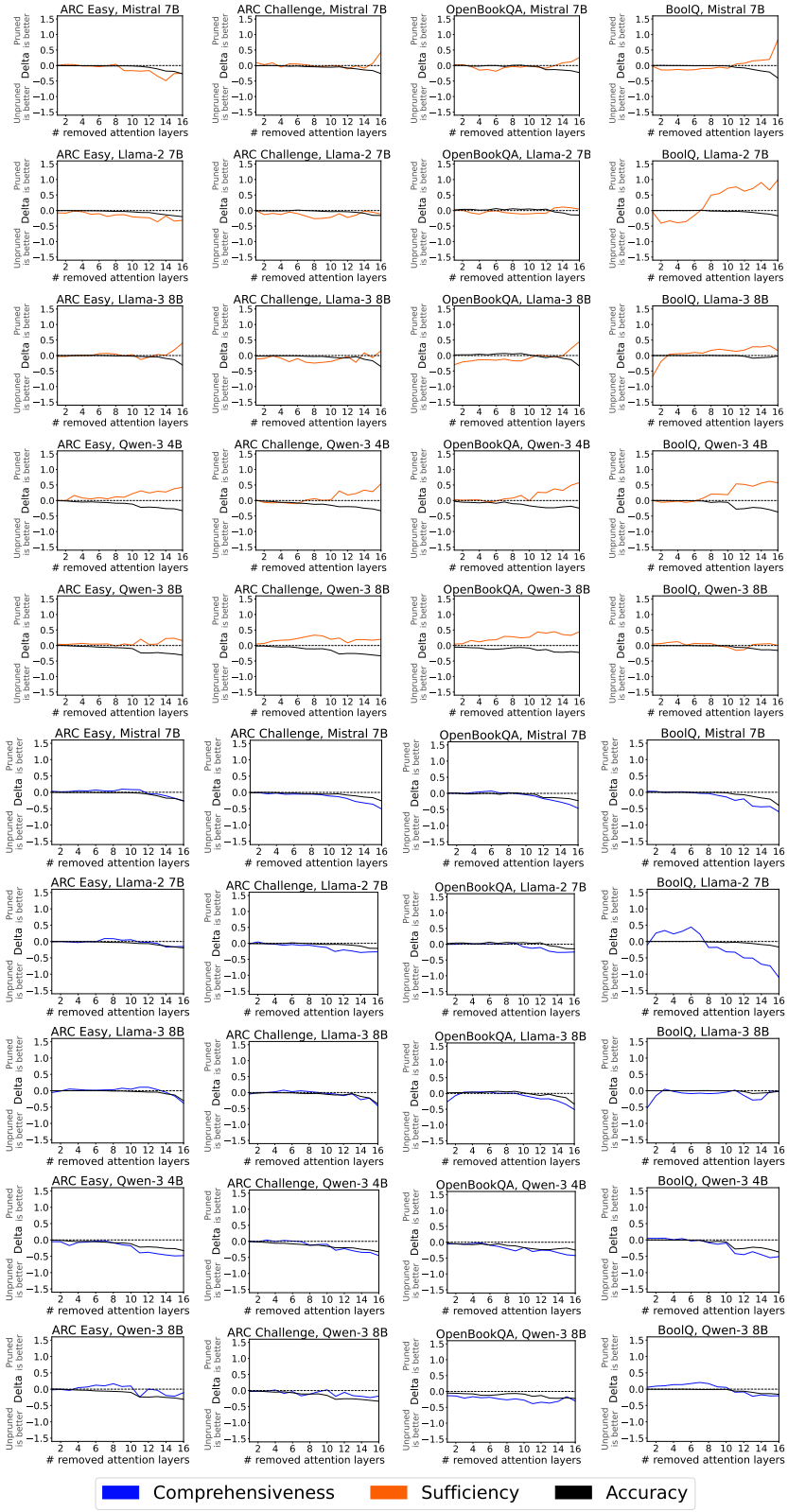

Figure 22: Relative reduction in comprehensiveness and sufficiency using Kernel SHAP, and accuracy (y axis) between pruned and unpruned models across varying levels of attention layer removal. Accuracy and comprehensiveness reductions are negated, so that negative effects appear on the lower side of the plot.

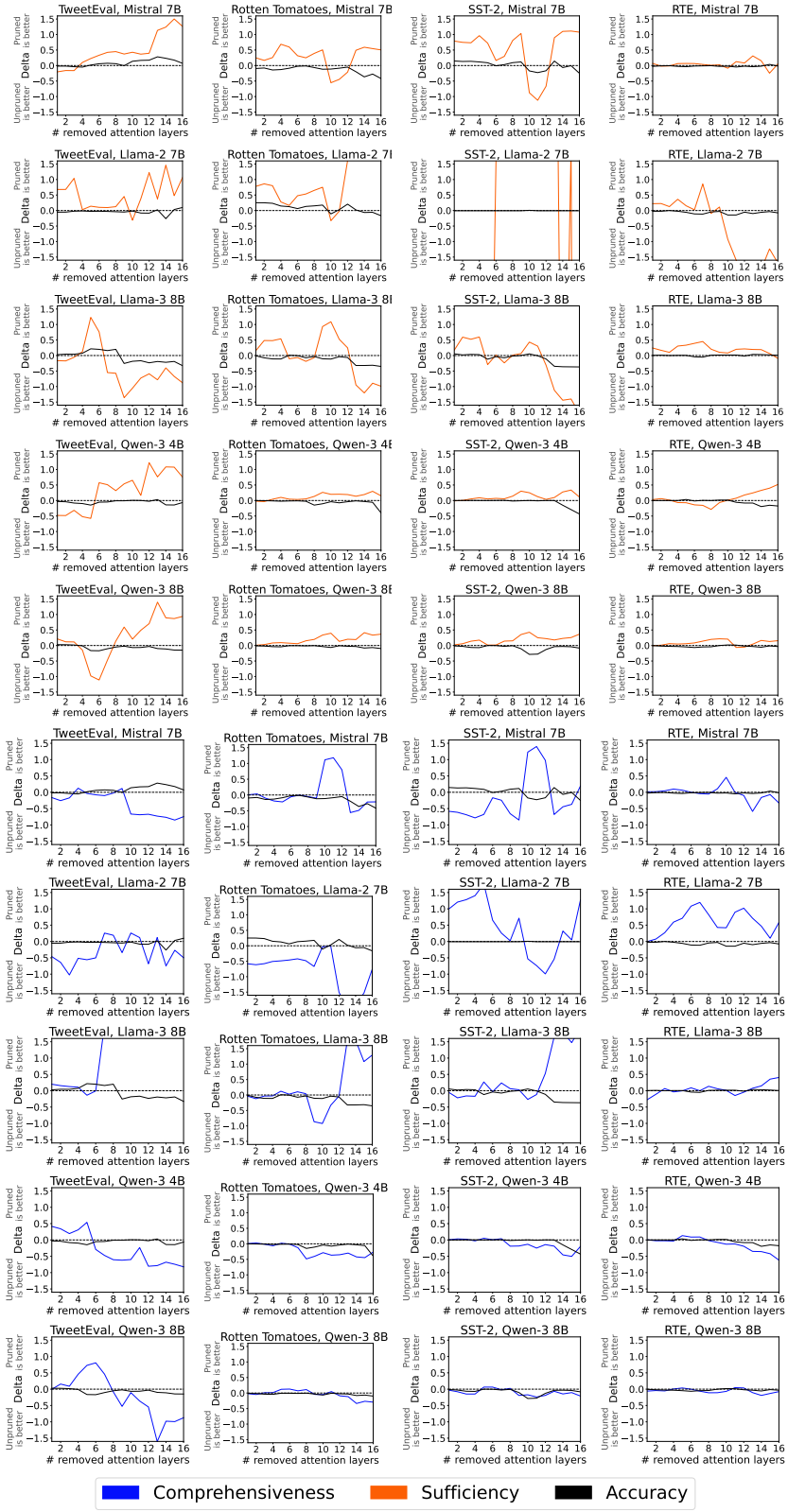

Figure 23: Relative reduction in comprehensiveness and sufficiency using Kernel SHAP, and accuracy (y axis) between pruned and unpruned models across varying levels of attention layer removal. Accuracy and comprehensiveness reductions are negated, so that negative effects appear on the lower side of the plot.

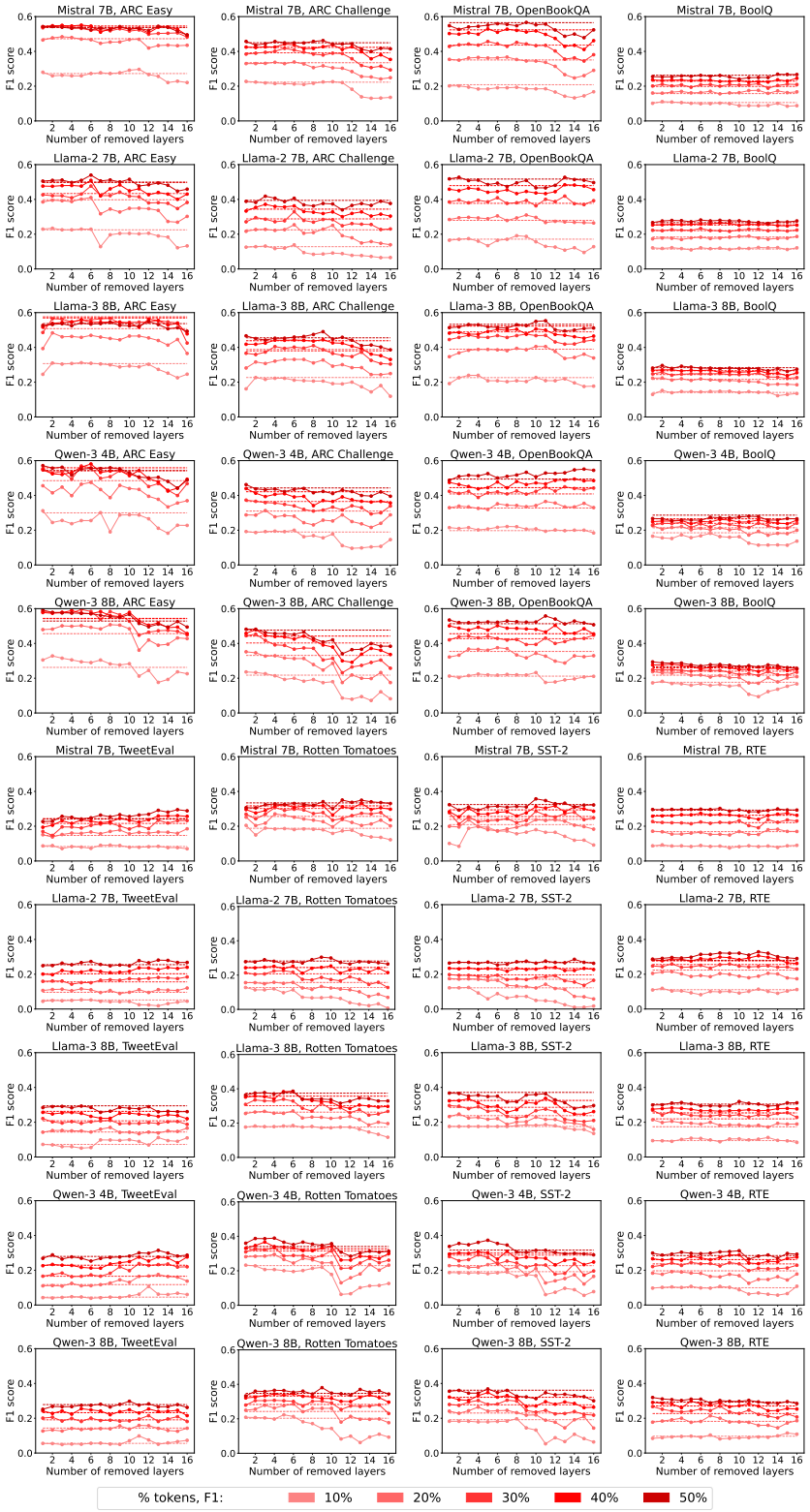

Figure 24: F1 score (y-axis) between LIME attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

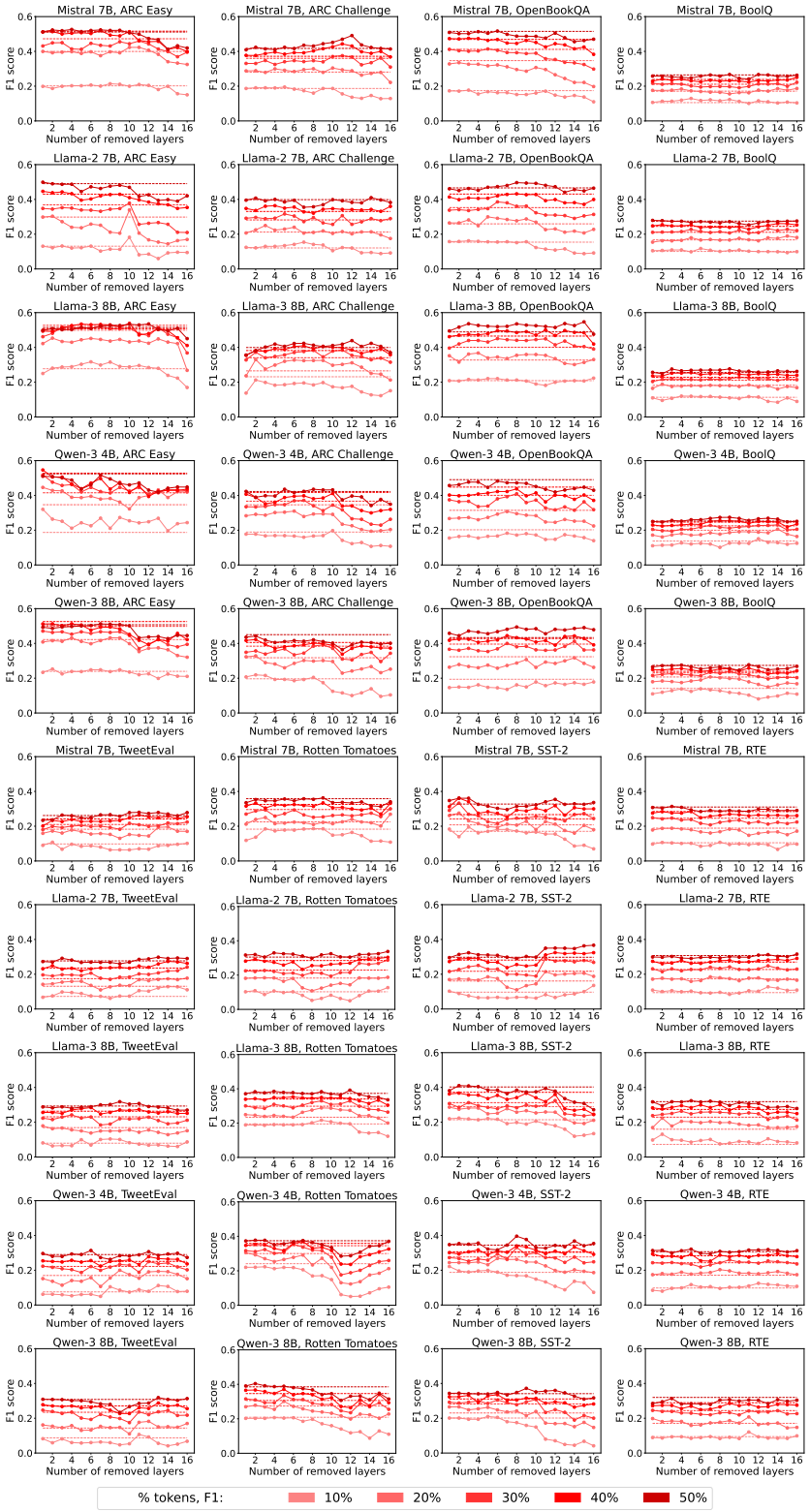

Figure 25: F1 score (y-axis) between Kernel SHAP attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

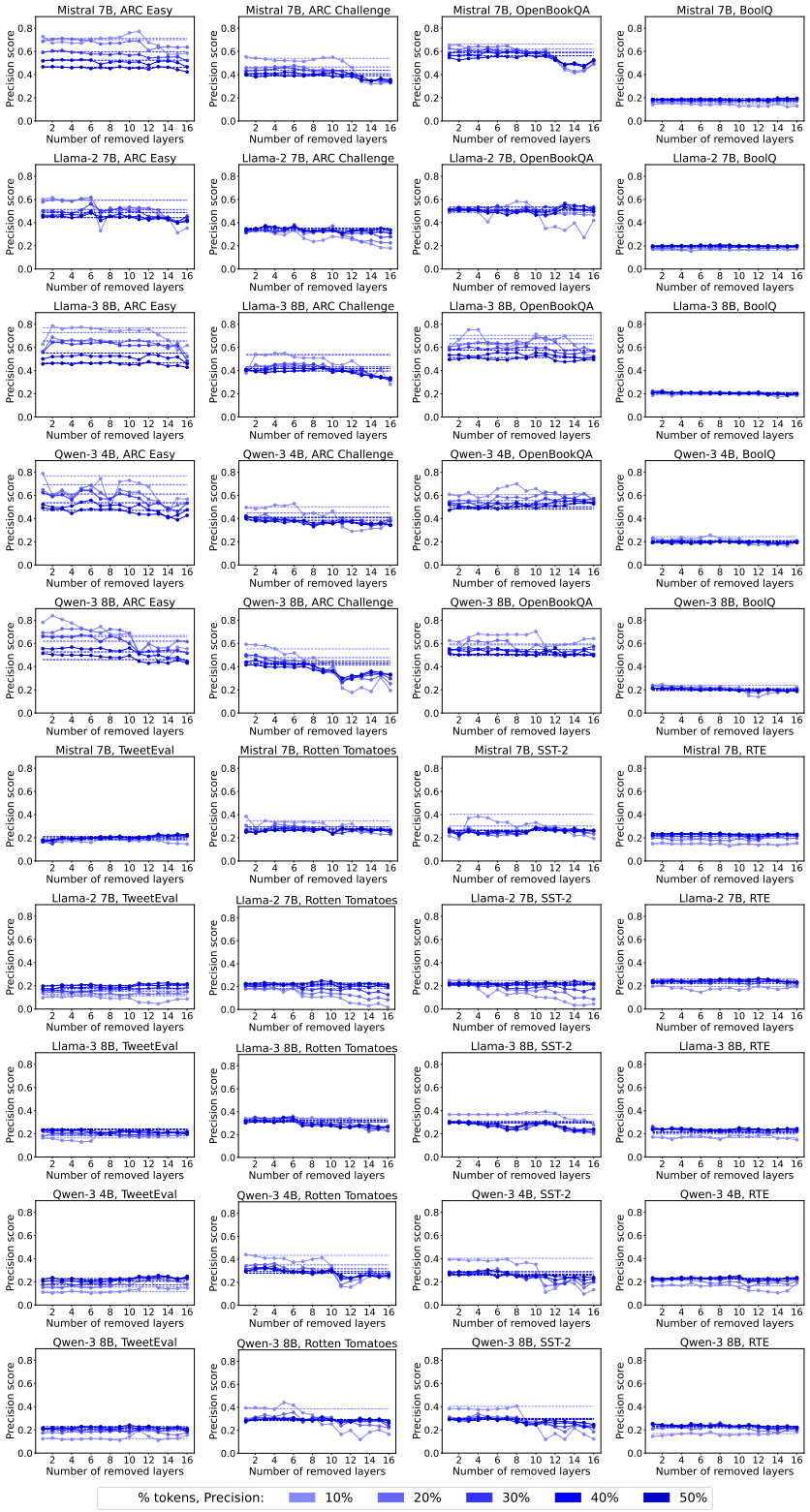

Figure 26: Precision (y-axis) between LIME attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

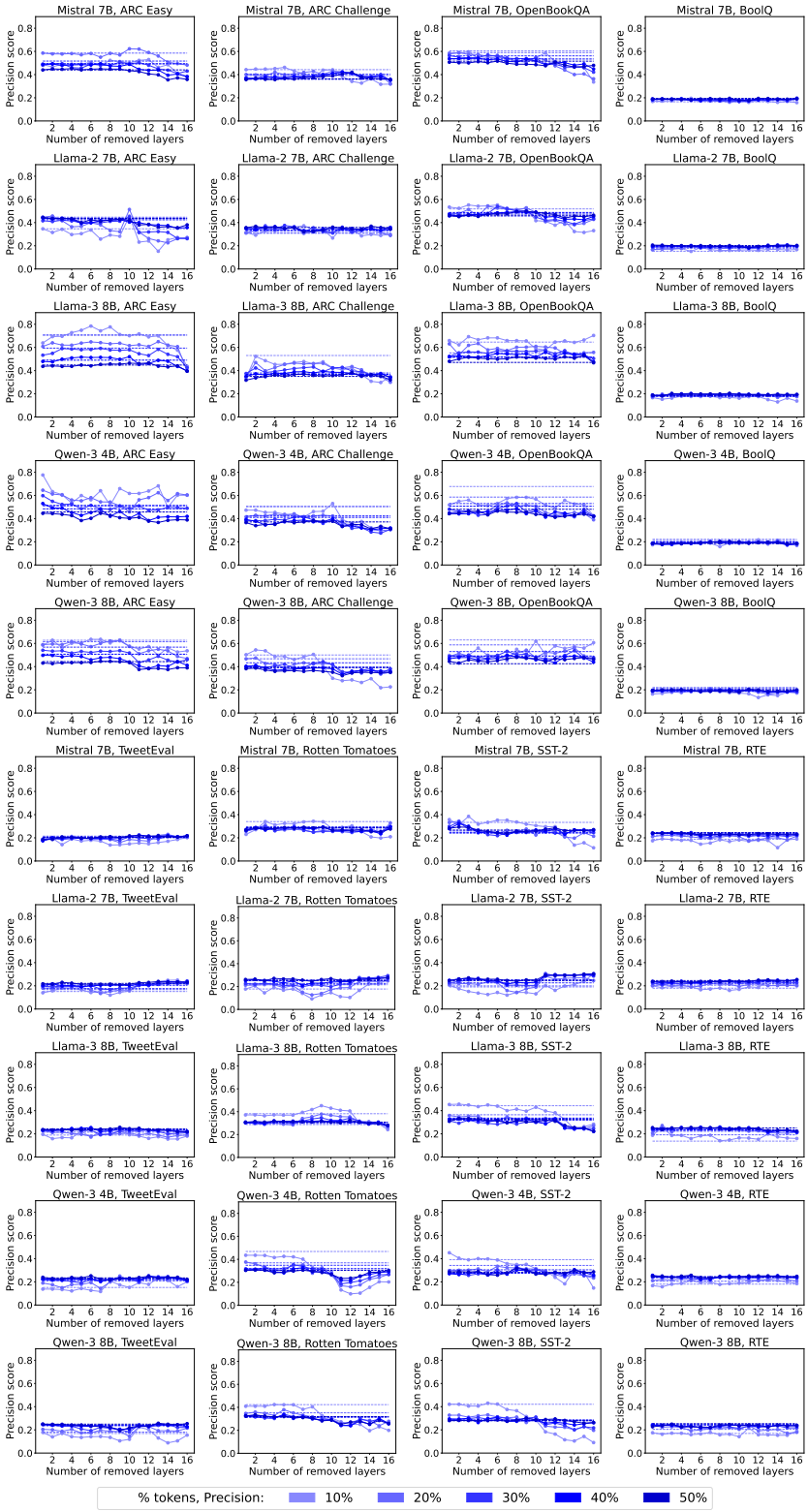

Figure 27: Precision (y-axis) between Kernel SHAP attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

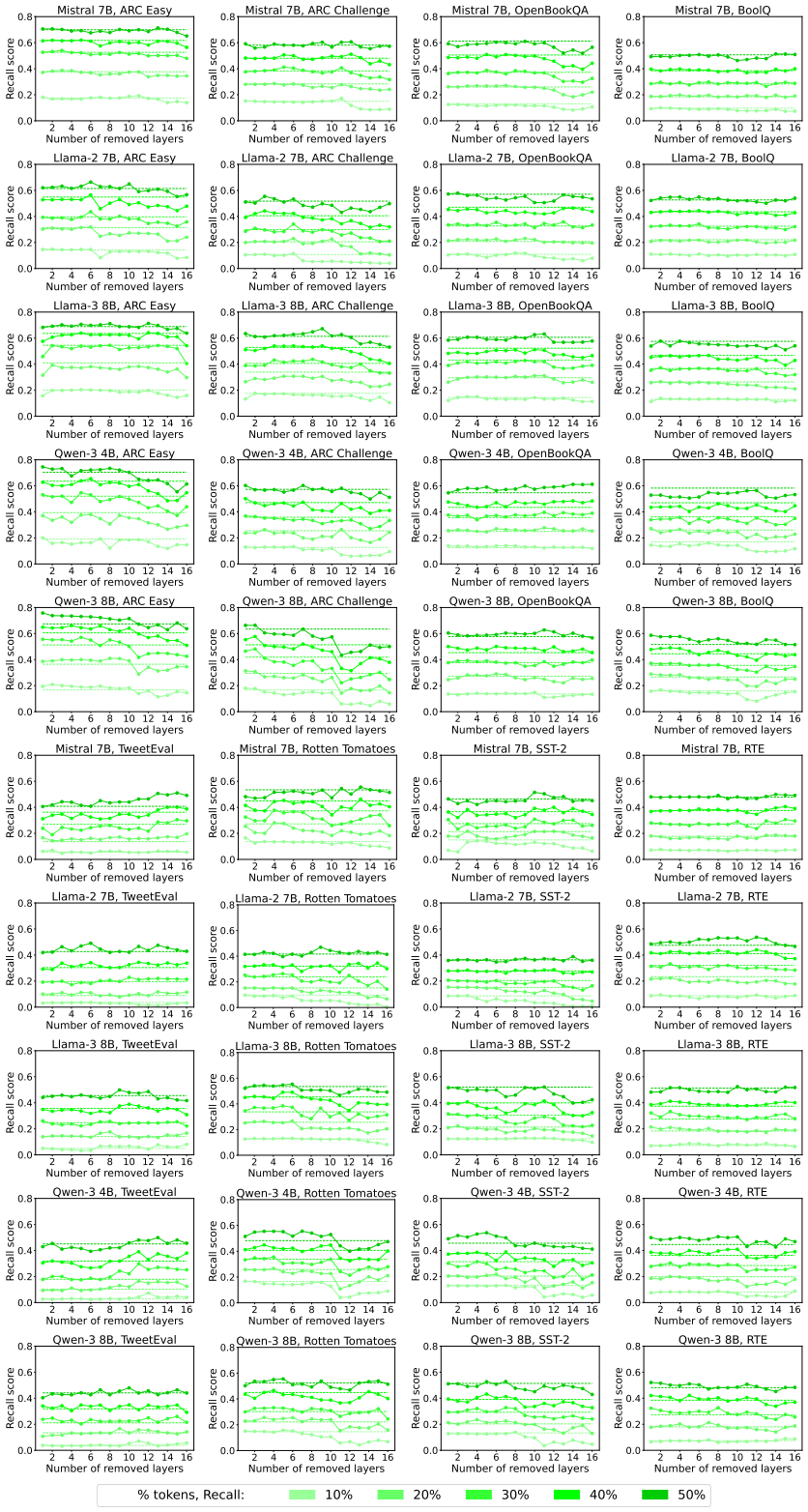

Figure 28: Recall (y-axis) between LIME attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

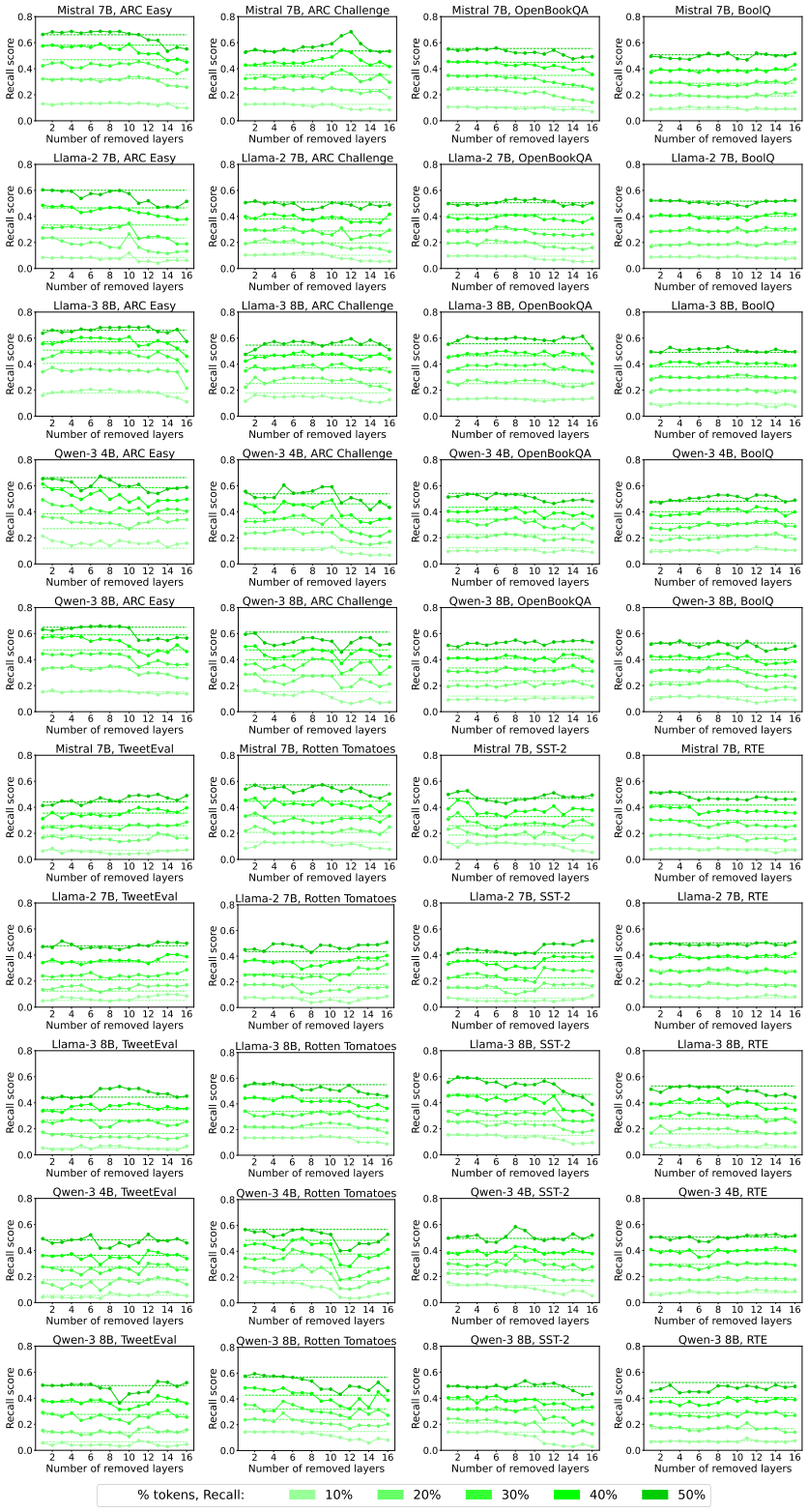

Figure 29: Recall (y-axis) between Kernel SHAP attributions and human annotations as a function of pruned attention layers (x-axis). Colours denote the proportion of top features considered (K), and dotted lines indicate unpruned models.

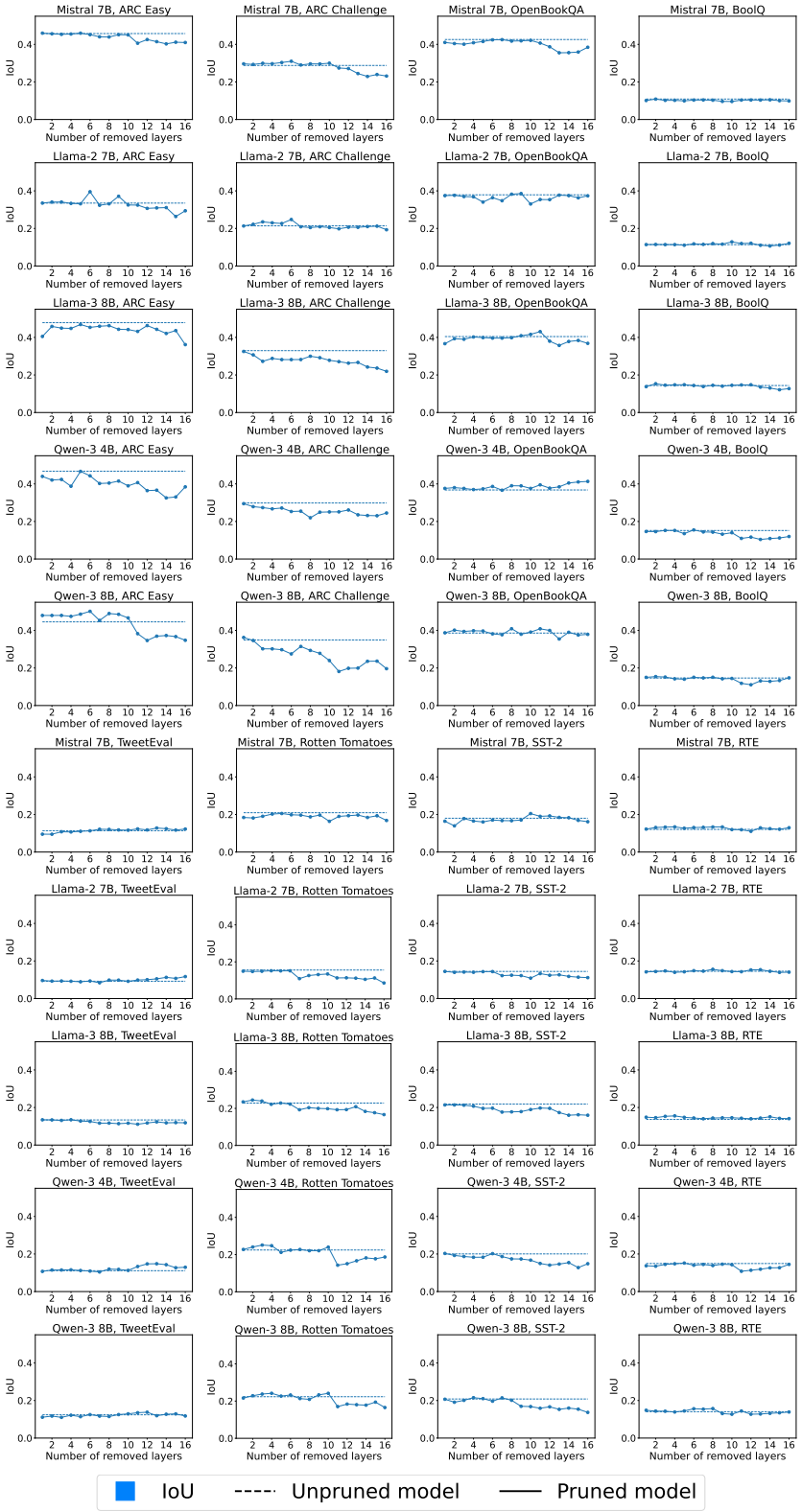

Figure 30: Intersection-over-Union (y-axis) between LIME attributions and human annotations as a function of pruned attention layers (x-axis). The dotted line denotes the unpruned model.

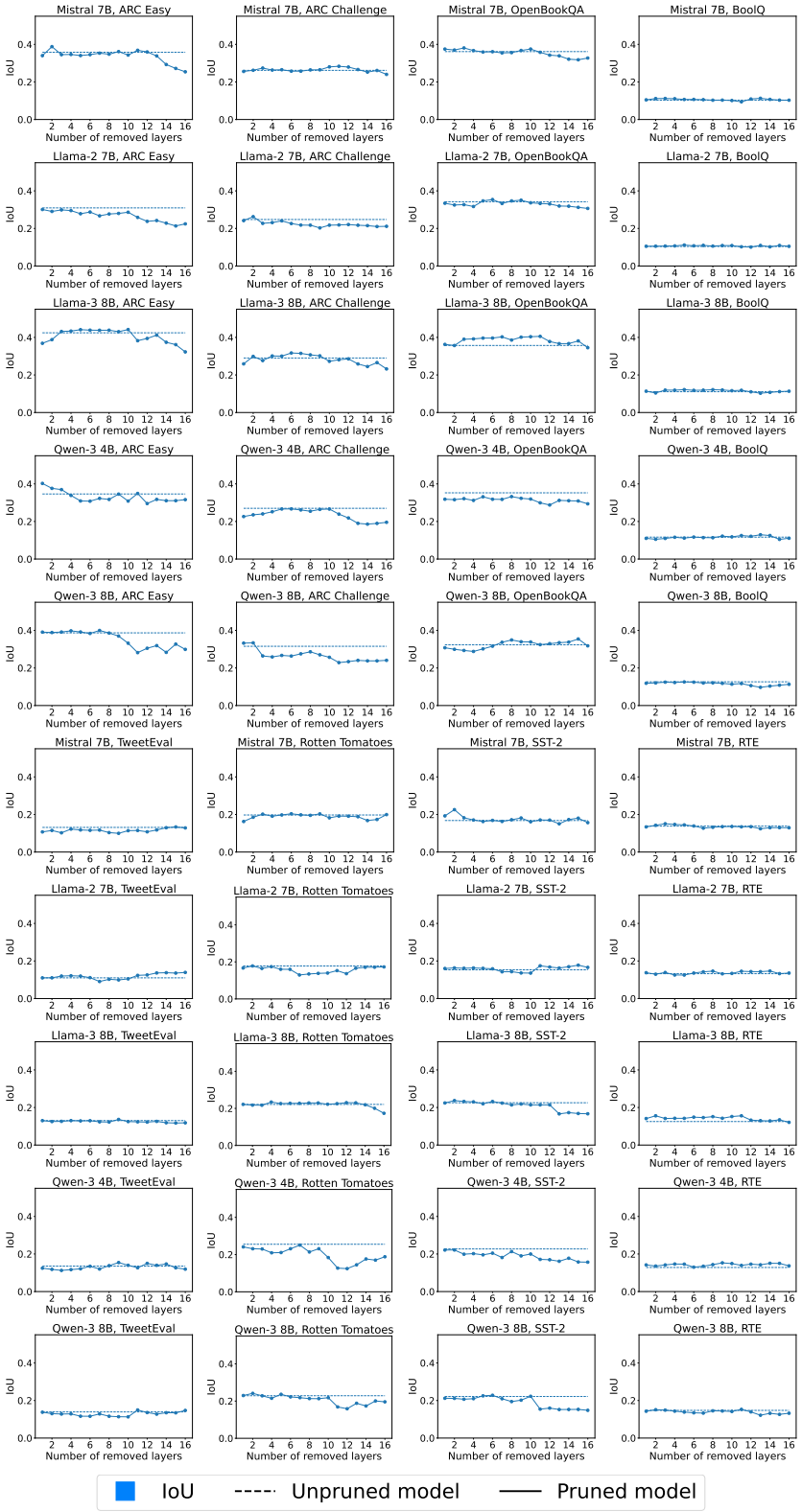

Figure 31: Intersection-over-Union (y-axis) between Kernel SHAP attributions and human annotations as a function of pruned attention layers (x-axis). The dotted line denotes the unpruned model.

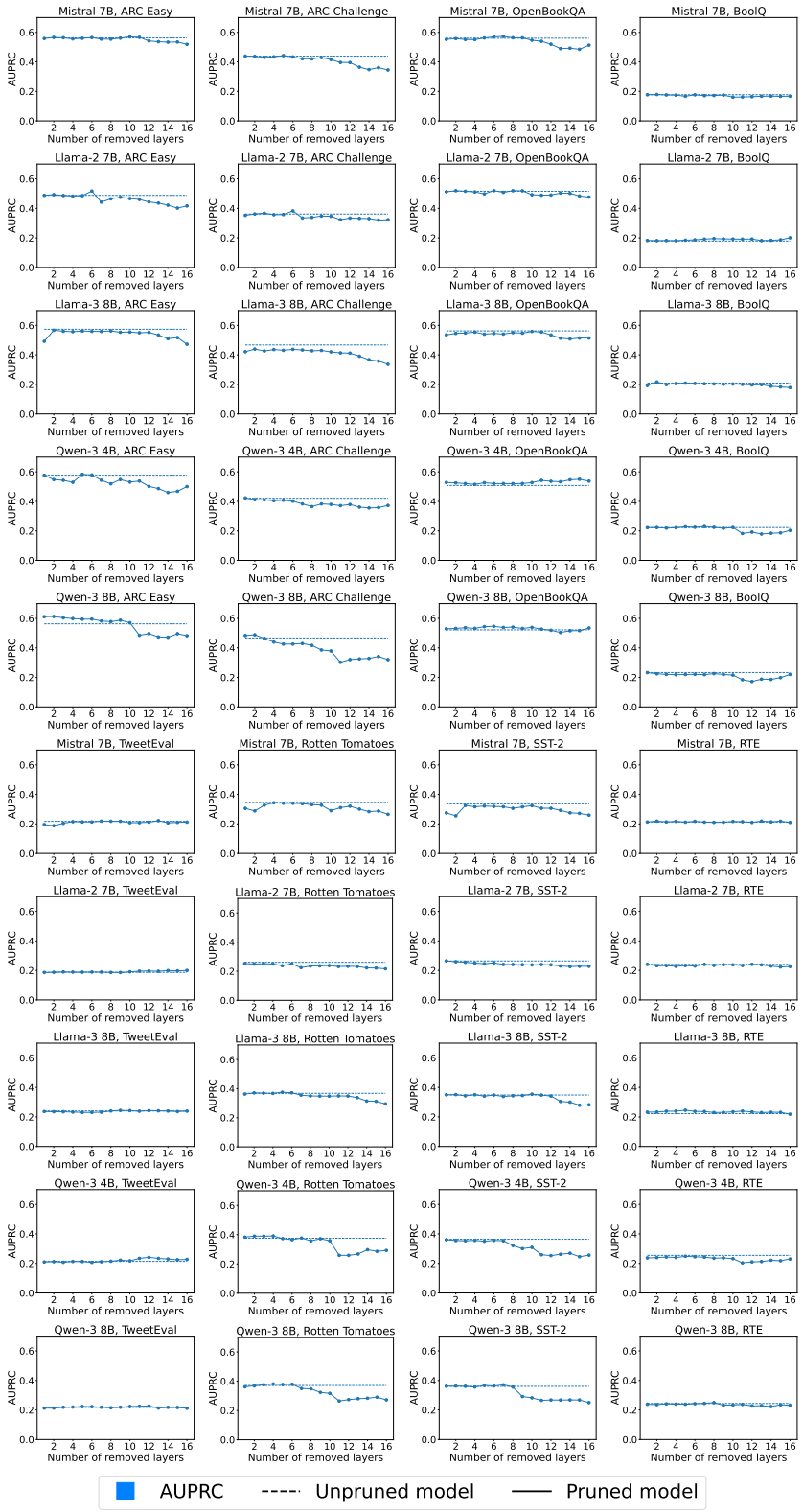

Figure 32: Area Under the Precision-Recall Curve (y-axis) between LIME attributions and human annotations as a function of pruned attention layers (x-axis). The dotted line denotes the unpruned model.

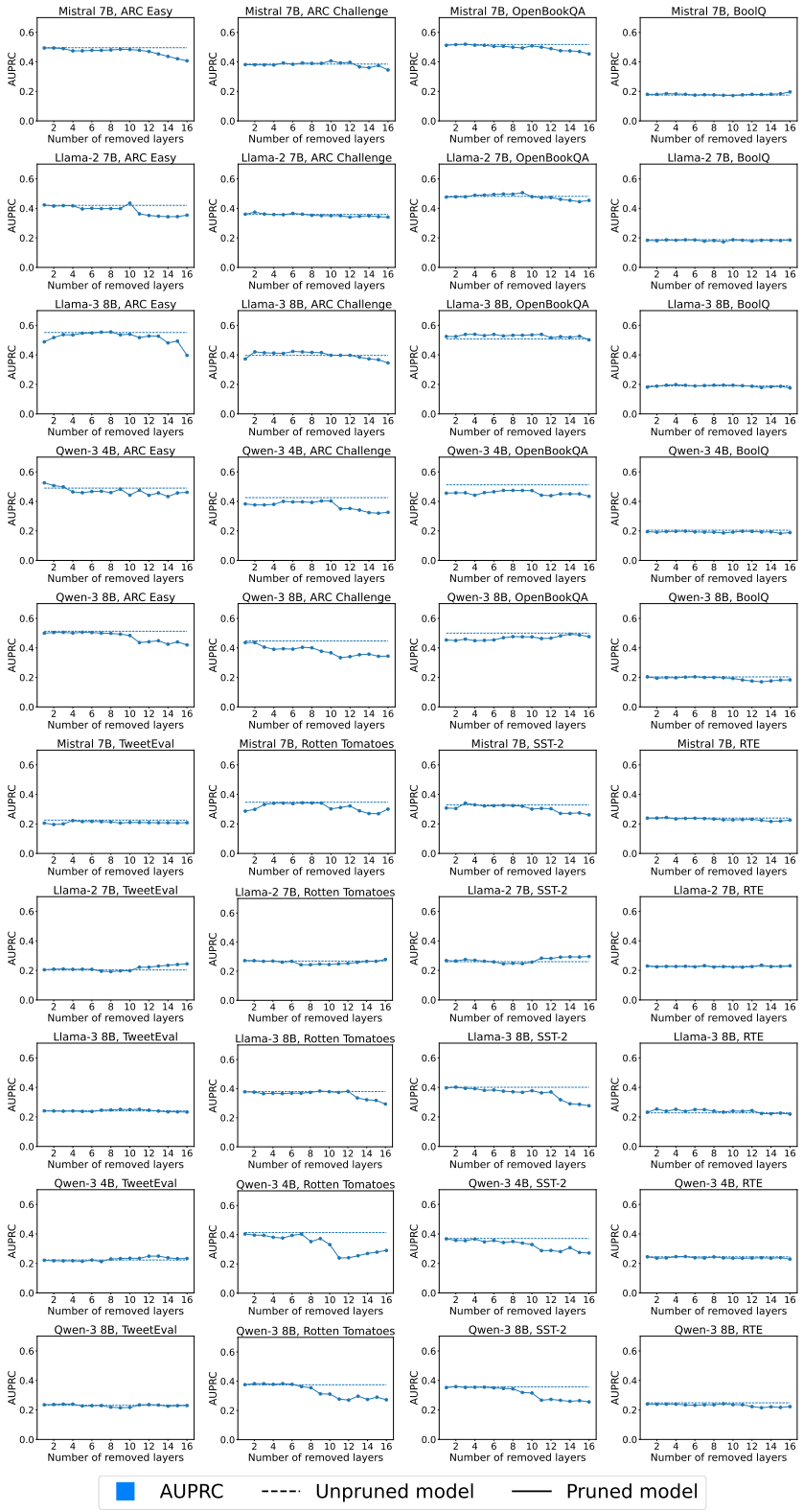

Figure 33: Area Under the Precision-Recall Curve (y-axis) between Kernel SHAP attributions and human annotations as a function of pruned attention layers (x-axis). The dotted line denotes the unpruned model.

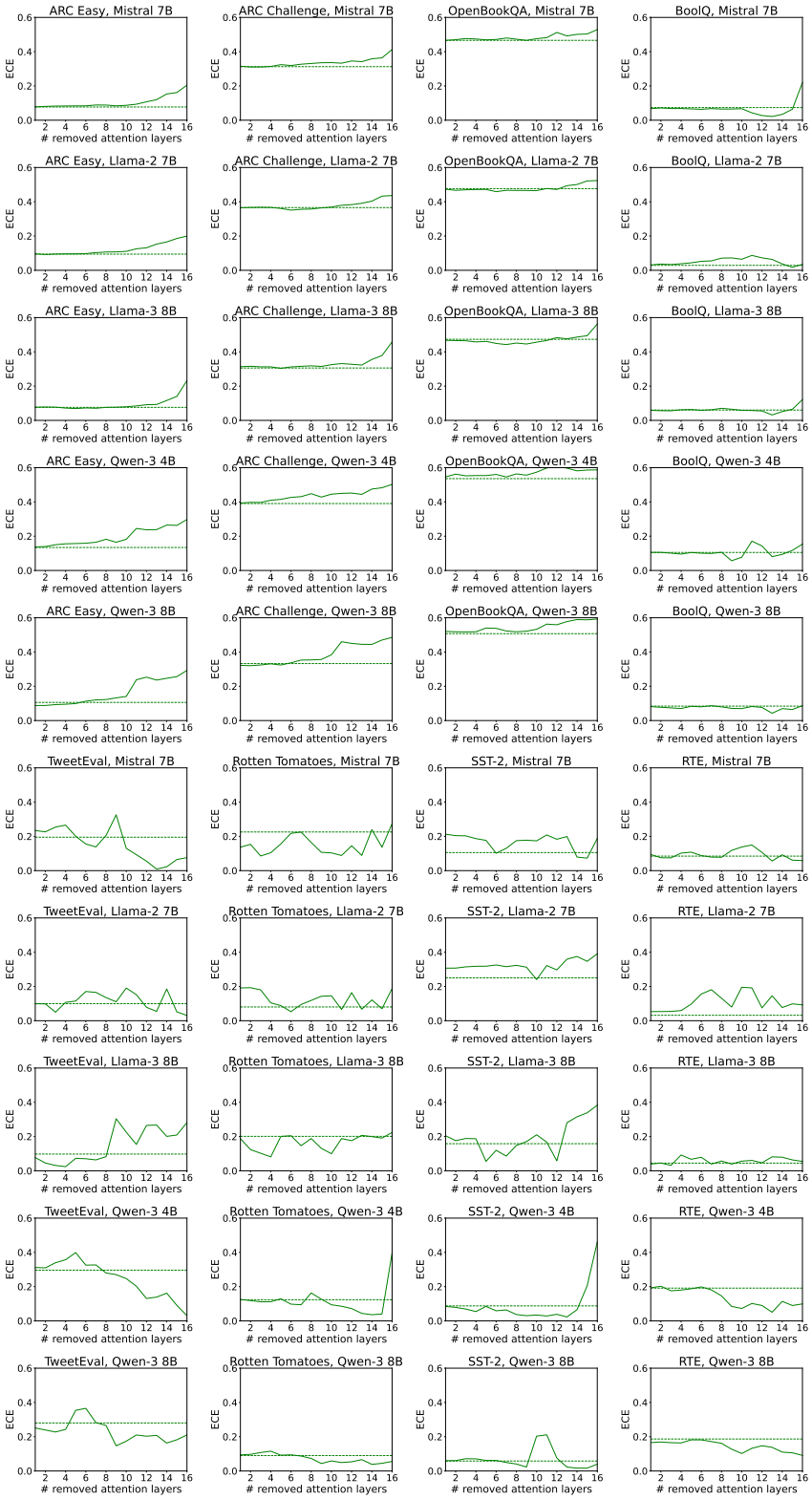

Figure 34: Expected Calibration Error (y axis) for Mistral (first row), Llama-2 (second row), Llama-3.1 (third row), Qwen3-4B (fourth row), and Qwen3-8B (fifth row) at different amounts of removed attention layers (x axis).

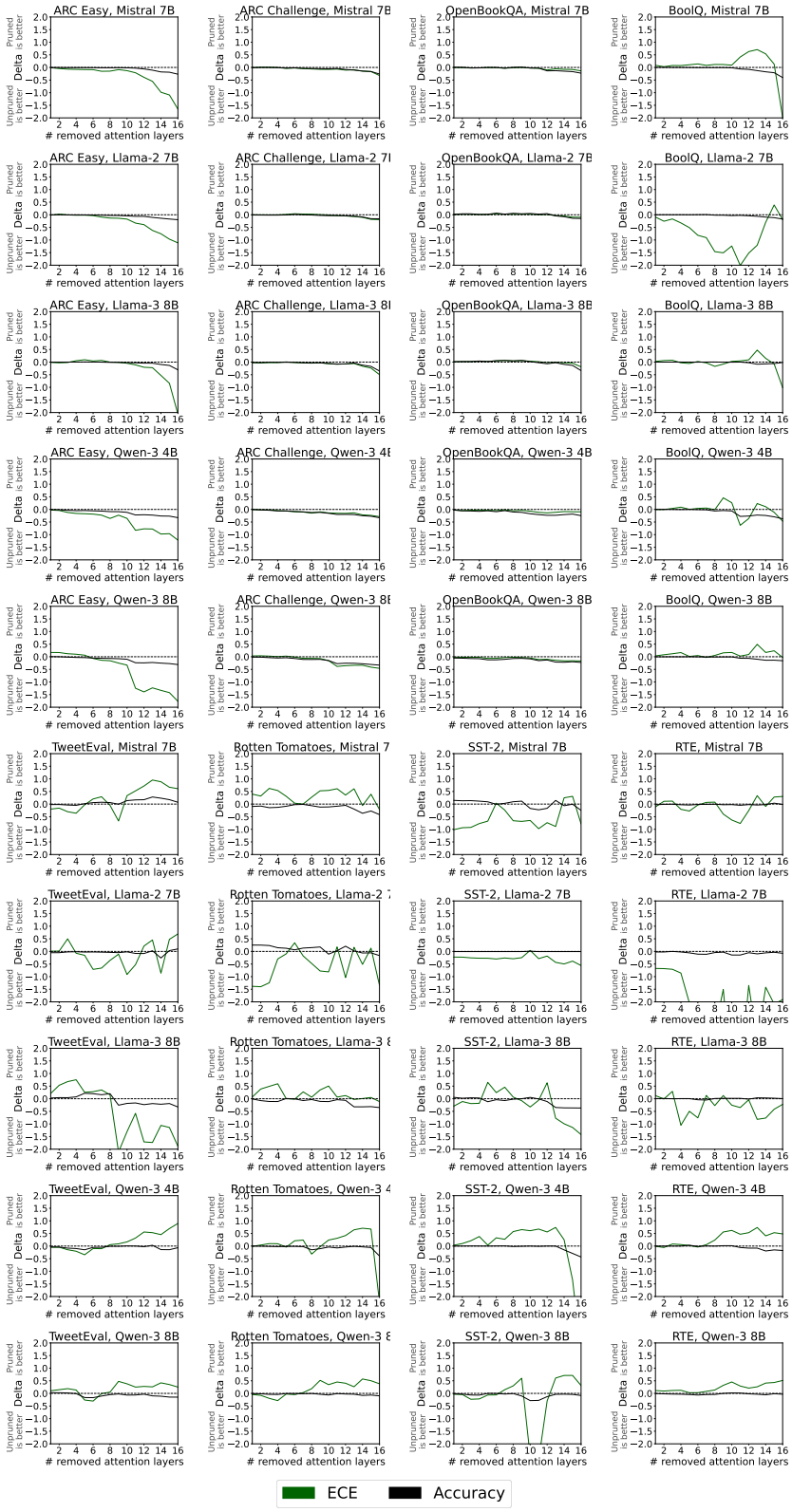

Figure 35: Relative reduction in ECE and accuracy (y axis) for Mistral (first row), Llama-2 (second row), Llama-3.1 (third row), Qwen3-4B (fourth row), and Qwen3-8B (fifth row) at different amounts of removed attention layers (x axis). Accuracy reductions are negated, so negative effects are on the plots' lower side.

Table 8: Results for Llama-2 on ARC Easy. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.763	0.233	0.190	0.215	0.211	0.094
1	0.761	0.234	0.189	0.213	0.214	0.096
2	0.763	0.236*	0.187	0.215	0.218	0.092
3	0.759	0.230	0.177*	0.212	0.212	0.095
4	0.760	0.235	0.180	0.208	0.215	0.096
5	0.758	0.235	0.179	0.214	0.219	0.096
6	0.756	0.236	0.172*	0.213	0.217	0.097
7	0.749*	0.244*	0.207*	0.234*	0.239*	0.103
8	0.742*	0.248*	0.204*	0.233*	0.234*	0.107
9	0.741*	0.237	0.197*	0.223	0.233*	0.107
10	0.731*	0.234	0.209*	0.226	0.236*	0.111
11	0.716*	0.214*	0.229*	0.211	0.249*	0.125
12	0.715*	0.215*	0.229*	0.209	0.254*	0.131
13	0.684*	0.211*	0.227*	0.203	0.250*	0.153
14	0.658*	0.177*	0.192	0.178*	0.217	0.165
15	0.635*	0.196*	0.206*	0.180*	0.236*	0.186
16	0.614*	0.200*	0.208*	0.182*	0.232*	0.199

Table 9: Results for Llama-2 on ARC Challenge. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.434	0.255	0.140	0.237	0.171	0.366
1	0.430	0.253	0.140	0.233	0.171	0.365
2	0.429	0.266*	0.152	0.248*	0.183*	0.367
3	0.428	0.260*	0.146	0.234	0.186*	0.368
4	0.428	0.258	0.151	0.231	0.186	0.367
5	0.432	0.252	0.143	0.223	0.182	0.361
6	0.441	0.255	0.149	0.228	0.187	0.351
7	0.434	0.249	0.161*	0.222	0.189*	0.356
8	0.430	0.244	0.162*	0.223*	0.187*	0.358
9	0.423	0.232	0.154*	0.214*	0.180	0.364
10	0.419	0.217*	0.153*	0.207	0.175	0.369
11	0.421	0.196*	0.160*	0.177*	0.185*	0.379
12	0.417	0.216*	0.167*	0.189*	0.197*	0.383
13	0.410*	0.197*	0.167*	0.180*	0.190	0.391
14	0.397*	0.182*	0.160	0.169*	0.178	0.404
15	0.367*	0.184*	0.172*	0.173*	0.182	0.433
16	0.365*	0.194*	0.160*	0.174*	0.175	0.436

Table 10: Results for Llama-2 on OpenBookQA. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.314	0.245	0.160	0.203	0.202	0.477
1	0.320	0.247	0.162	0.202	0.203	0.473
2	0.326	0.247	0.164	0.203	0.204	0.467
3	0.326	0.255	0.170	0.208	0.215	0.470
4	0.318	0.250	0.171	0.206	0.218	0.471
5	0.320	0.247	0.169	0.205	0.215	0.472
6	0.334*	0.247	0.171	0.205	0.215	0.459
7	0.322	0.243	0.176*	0.205	0.211	0.467
8	0.332	0.243	0.184*	0.204	0.212	0.466
9	0.326	0.246	0.186*	0.212	0.217	0.466
10	0.330	0.221*	0.178*	0.186*	0.215	0.465
11	0.322	0.218*	0.180*	0.177*	0.212	0.477
12	0.328	0.221*	0.185*	0.182*	0.213	0.472
13	0.300	0.182*	0.161	0.159*	0.188	0.494
14	0.290	0.182*	0.161	0.150*	0.181	0.501
15	0.270*	0.172*	0.155	0.151*	0.179	0.522
16	0.268*	0.162*	0.168*	0.153*	0.178	0.524

Table 11: Results for Llama-2 on BoolQ. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.777	0.282	0.092	0.118	0.153	0.029
1	0.777	0.267*	0.105*	0.104*	0.157	0.031
2	0.779	0.275	0.119*	0.148*	0.191*	0.036
3	0.778	0.312*	0.117*	0.157*	0.198*	0.034
4	0.779	0.294*	0.104*	0.145*	0.205*	0.038
5	0.777	0.294*	0.087	0.155*	0.181*	0.044
6	0.780	0.293*	0.122*	0.170*	0.154	0.052
7	0.783	0.232*	0.104*	0.145*	0.137	0.055
8	0.765	0.112*	0.072	0.096	0.067*	0.071
9	0.763	0.102*	0.073	0.097	0.058*	0.072
10	0.753*	0.084*	0.075	0.080	0.046*	0.065
11	0.759*	0.095*	0.055*	0.079	0.038*	0.087
12	0.747*	0.076*	0.048*	0.059*	0.047*	0.073
13	0.730*	0.065*	-0.022*	0.058*	0.022*	0.064
14	0.706*	0.054*	-0.018*	0.036*	-0.006*	0.037
15	0.688*	0.043*	-0.033*	0.030*	-0.008*	0.018
16	0.646*	-0.004*	-0.042*	-0.012*	-0.035*	0.034

Table 12: Results for Llama-2 on TweetEval. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.482	0.072	0.133	0.086	0.128	0.100
1	0.458*	0.038*	0.048*	0.046*	0.041*	0.099
2	0.458*	0.016*	0.055*	0.031*	0.041*	0.098
3	0.472	-0.017*	-0.000*	-0.002*	-0.005*	0.050
4	0.476	0.017*	0.123	0.042*	0.125	0.107
5	0.470*	0.021*	0.091	0.038*	0.110*	0.115
6	0.471*	0.032*	0.086*	0.043*	0.115	0.171
7	0.469*	0.122*	0.094*	0.109*	0.116	0.165
8	0.464*	0.110*	0.095*	0.103*	0.112	0.135
9	0.459*	0.056*	0.054*	0.057*	0.070*	0.111
10	0.474	0.131*	0.137	0.109*	0.168*	0.191
11	0.444*	0.160*	0.060*	0.097*	0.080	0.152
12	0.442*	0.052	-0.035*	0.027*	-0.029*	0.078
13	0.494	0.188*	0.067*	0.097*	0.081	0.054
14	0.356*	0.081	-0.057*	0.022*	-0.059*	0.185
15	0.498	0.139*	0.072*	0.063*	0.067*	0.052
16	0.530*	0.006*	-0.045*	0.043*	-0.008*	0.031

Table 13: Results for Llama-2 on Rotten Tomatoes. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.623	0.092	0.128	0.105	0.136	0.080
1	0.780*	0.046*	0.038*	0.044*	0.030*	0.192
2	0.779*	0.043*	0.030*	0.041*	0.019*	0.193
3	0.768*	0.047*	0.037*	0.044*	0.027*	0.180
4	0.714*	0.044*	0.098	0.052*	0.098	0.104
5	0.701*	0.046*	0.099	0.054*	0.114*	0.088
6	0.662*	0.049*	0.060*	0.057*	0.071*	0.053
7	0.705*	0.059*	0.057*	0.061*	0.064*	0.095
8	0.717*	0.052*	0.041*	0.054*	0.048*	0.119
9	0.733*	0.034*	0.025*	0.035*	0.034*	0.143
10	0.555*	0.083*	0.171*	0.101*	0.181*	0.145
11	0.641	0.100*	0.127*	0.105	0.139*	0.066
12	0.751*	-0.067*	-0.110*	-0.053*	-0.083*	0.164
13	0.635	-0.153*	-0.213*	-0.110*	-0.174*	0.067
14	0.583	-0.111*	-0.261*	-0.093*	-0.208*	0.122
15	0.587	-0.052*	-0.193*	-0.056*	-0.159*	0.070
16	0.520*	0.072*	-0.132*	0.026*	-0.099*	0.188

Table 14: Results for Llama-2 on SST-2. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.494	0.108	0.052	0.084	0.002	0.250
1	0.491	0.200*	0.097*	0.168*	0.060*	0.307
2	0.491	0.220*	0.101*	0.186*	0.063*	0.307
3	0.491	0.227*	0.093*	0.192*	0.055*	0.315
4	0.491	0.233*	0.074*	0.202*	0.036*	0.318
5	0.491	0.271*	0.062*	0.233*	0.033*	0.318
6	0.491	0.176*	0.046	0.139*	-0.001	0.325
7	0.491	0.139*	-0.027*	0.106*	-0.040*	0.316
8	0.491	0.123*	-0.081*	0.086	-0.076*	0.323
9	0.491	0.178*	-0.090*	0.144*	-0.089*	0.313
10	0.498	0.080*	-0.141*	0.040*	-0.112*	0.240
11	0.491	0.023*	-0.106*	0.022*	-0.063*	0.322
12	0.491	-0.012*	-0.110*	0.001*	-0.069*	0.297
13	0.491	0.004*	-0.057*	0.039*	-0.027*	0.359
14	0.491	0.110	-0.006*	0.111*	0.029*	0.375
15	0.491	0.112	-0.011*	0.088	-0.002	0.347
16	0.491	0.246*	0.115*	0.191*	0.132*	0.391

Table 15: Results for Llama-2 on RTE. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.628	0.092	0.040	0.078	0.043	0.032
1	0.614	0.098*	0.023*	0.078	0.032*	0.053
2	0.614	0.104*	0.029*	0.084*	0.039	0.054
3	0.628	0.119*	0.050*	0.099*	0.048	0.054
4	0.614	0.153*	0.014*	0.125*	0.025*	0.059
5	0.592	0.168*	0.040*	0.134*	0.055*	0.097
6	0.560*	0.191*	0.059*	0.163*	0.082*	0.156
7	0.556*	0.211*	-0.007*	0.172*	0.035	0.181
8	0.599	0.179*	0.056*	0.143*	0.082*	0.131
9	0.610	0.152*	0.030	0.112*	0.061*	0.080
10	0.538*	0.212*	0.106*	0.111*	0.151*	0.195
11	0.538*	0.254*	0.163*	0.149*	0.220*	0.192
12	0.596	0.217*	0.187*	0.158*	0.210*	0.075
13	0.567*	0.182*	0.147*	0.134*	0.212*	0.146
14	0.592	0.178*	0.095*	0.115*	0.163*	0.077
15	0.606	0.150*	0.070*	0.086	0.137*	0.098
16	0.581	0.209*	0.083*	0.124*	0.159*	0.093

Table 16: Results for Mistral on ARC Easy. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.809	0.266	0.155	0.254	0.200	0.077
1	0.808	0.276*	0.160*	0.262*	0.204	0.078
2	0.806	0.272*	0.154	0.258*	0.199	0.081
3	0.803	0.271*	0.157*	0.259*	0.202	0.082
4	0.804	0.278*	0.160*	0.266*	0.206	0.083
5	0.803	0.280*	0.158	0.264	0.205	0.084
6	0.802	0.289*	0.161	0.271*	0.213*	0.084
7	0.798*	0.284*	0.163	0.264	0.209*	0.089
8	0.798*	0.280*	0.160	0.264*	0.205*	0.089
9	0.801	0.294*	0.179*	0.278*	0.228*	0.084
10	0.796*	0.294*	0.173*	0.275*	0.220*	0.087
11	0.786*	0.295*	0.183*	0.273*	0.226*	0.093
12	0.761*	0.270*	0.174*	0.242	0.212*	0.107
13	0.721*	0.264	0.180*	0.240	0.207*	0.120
14	0.665*	0.248	0.176*	0.226*	0.206	0.153
15	0.656*	0.238	0.166*	0.207*	0.195	0.161
16	0.592*	0.213*	0.155	0.188*	0.177	0.205

Table 17: Results for Mistral on ARC Challenge. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.504	0.278	0.141	0.257	0.175	0.313
1	0.500	0.273*	0.136	0.254	0.169*	0.315
2	0.504	0.269*	0.136	0.255	0.171	0.310
3	0.503	0.266*	0.135	0.246*	0.167*	0.311
4	0.501	0.271	0.144	0.251	0.177	0.314
5	0.492	0.260*	0.135	0.243*	0.166	0.324
6	0.496	0.263*	0.141	0.244*	0.171	0.319
7	0.486*	0.256*	0.139	0.244*	0.171	0.327
8	0.484*	0.257*	0.147	0.243*	0.177	0.331
9	0.480*	0.254*	0.148	0.240*	0.183	0.336
10	0.477*	0.244*	0.142	0.229*	0.175	0.336
11	0.483*	0.246*	0.142	0.224*	0.177	0.333
12	0.464*	0.231*	0.137	0.210*	0.169	0.346
13	0.451*	0.204*	0.127	0.186*	0.159	0.342
14	0.433*	0.188*	0.124	0.174*	0.151	0.359
15	0.423*	0.187*	0.114	0.164*	0.155	0.364
16	0.373*	0.148*	0.091*	0.126*	0.120*	0.413

Table 18: Results for Mistral on OpenBookQA. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.326	0.259	0.171	0.230	0.203	0.466
1	0.328	0.259	0.171	0.232	0.201	0.466
2	0.328	0.260	0.162	0.231	0.201*	0.470
3	0.320	0.256	0.165	0.229	0.202*	0.477
4	0.320	0.260	0.176	0.237*	0.210*	0.474
5	0.326	0.265*	0.178	0.242*	0.215*	0.469
6	0.326	0.265	0.190*	0.247*	0.222*	0.471
7	0.316	0.255	0.176	0.233	0.206	0.480
8	0.328	0.258	0.182*	0.235	0.213	0.473
9	0.330	0.253	0.190*	0.228	0.219	0.466
10	0.318	0.246	0.177*	0.221	0.205	0.476
11	0.318	0.233*	0.170*	0.211	0.195	0.482
12	0.282*	0.218*	0.155	0.193*	0.176	0.512
13	0.284*	0.203*	0.152	0.181*	0.176*	0.492
14	0.278*	0.182*	0.140*	0.168*	0.159*	0.501
15	0.272*	0.167*	0.131*	0.151*	0.146*	0.503
16	0.252*	0.139*	0.115*	0.124*	0.125*	0.529

Table 19: Results for Mistral on BoolQ. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.836	0.344	0.145	0.315	0.175	0.074
1	0.836	0.347*	0.150*	0.325*	0.178	0.067
2	0.839	0.342	0.153*	0.323*	0.181*	0.072
3	0.835	0.333	0.154*	0.313	0.185*	0.068
4	0.835	0.334	0.154*	0.317	0.182*	0.068
5	0.833	0.326*	0.158*	0.320	0.180*	0.066
6	0.829	0.318*	0.159*	0.314	0.178	0.063
7	0.831	0.317*	0.157*	0.304*	0.177	0.068
8	0.830	0.316*	0.157*	0.303*	0.180*	0.065
9	0.831	0.305*	0.154*	0.286*	0.180*	0.065
10	0.824*	0.286*	0.153*	0.270*	0.178	0.067
11	0.785*	0.219*	0.139	0.236*	0.162	0.043
12	0.772*	0.195*	0.140	0.251*	0.158	0.027
13	0.731*	0.149*	0.105*	0.181*	0.112*	0.022
14	0.691*	0.123*	0.104*	0.174*	0.102*	0.034
15	0.661*	0.104*	0.102*	0.178*	0.088*	0.064
16	0.501*	-0.003*	0.053*	0.127*	0.004*	0.220

Table 20: Results for Mistral on TweetEval. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.457	0.214	0.464	0.282	0.368	0.195
1	0.449*	0.191*	0.462*	0.237*	0.443*	0.234
2	0.449*	0.172*	0.438*	0.210*	0.427*	0.226
3	0.440*	0.182*	0.468*	0.234*	0.428*	0.254
4	0.434*	0.238*	0.448*	0.318*	0.331*	0.266
5	0.465*	0.210	0.373*	0.272*	0.285*	0.201
6	0.483*	0.225*	0.303*	0.261*	0.246*	0.156
7	0.490*	0.230*	0.251*	0.254*	0.211*	0.138
8	0.484*	0.268*	0.221*	0.275	0.203*	0.205
9	0.455	0.310*	0.251*	0.315*	0.231*	0.326
10	0.520*	0.069*	0.245*	0.094*	0.210*	0.130
11	0.533*	0.072*	0.260*	0.088*	0.233*	0.093
12	0.536*	0.077*	0.265*	0.092*	0.222*	0.055
13	0.586*	0.054*	-0.047*	0.076*	-0.049*	0.009
14	0.564*	0.061*	-0.104*	0.066*	-0.088*	0.022
15	0.537*	0.041*	-0.212*	0.042*	-0.185*	0.065
16	0.490	0.064*	-0.108*	0.072*	-0.097*	0.076

Table 21: Results for Mistral on Rotten Tomatoes. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.858	0.097	0.111	0.097	0.119	0.226
1	0.777*	0.100	0.109	0.098	0.089*	0.137
2	0.791*	0.104	0.115	0.101	0.099*	0.154
3	0.735*	0.106	0.096	0.087	0.088*	0.085
4	0.747*	0.079	0.033*	0.079	0.037*	0.104
5	0.784*	0.075	0.048*	0.076*	0.048*	0.156
6	0.839	0.091	0.080*	0.092	0.081*	0.218
7	0.847	0.099	0.088*	0.097	0.089*	0.225
8	0.803*	0.098	0.076*	0.092	0.072*	0.164
9	0.756*	0.093	0.061*	0.087	0.059*	0.107
10	0.761*	0.205*	0.200*	0.206*	0.184*	0.104
11	0.785*	0.228*	0.194*	0.212*	0.172*	0.088
12	0.815*	0.192*	0.155*	0.175*	0.144*	0.145
13	0.688*	0.033*	0.060*	0.043*	0.060*	0.089
14	0.545*	0.016*	0.055*	0.050*	0.049*	0.238
15	0.623*	0.055*	0.054*	0.076	0.054*	0.137
16	0.500*	0.026*	0.069*	0.076*	0.059*	0.275

Table 22: Results for Mistral on SST-2. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.689	0.110	0.126	0.111	0.137	0.105
1	0.790*	0.049*	0.029*	0.046*	0.029*	0.213
2	0.780*	0.051*	0.028*	0.043*	0.035*	0.204
3	0.783*	0.045*	0.027*	0.035*	0.037*	0.203
4	0.769*	0.042*	0.006*	0.024*	0.005*	0.187
5	0.751*	0.043*	0.039*	0.036*	0.038*	0.177
6	0.683	0.094*	0.110*	0.092*	0.115*	0.101
7	0.710	0.086*	0.094*	0.084*	0.096*	0.130
8	0.753*	0.047*	0.029*	0.038*	0.026*	0.175
9	0.769*	0.033*	-0.004*	0.017*	-0.005*	0.178
10	0.570*	0.275*	0.254*	0.247*	0.257*	0.174
11	0.532*	0.314*	0.269*	0.266*	0.291*	0.208
12	0.573*	0.269*	0.217*	0.219*	0.228*	0.183
13	0.789*	0.028*	0.008*	0.035*	0.014*	0.199
14	0.644	0.041*	-0.009*	0.062*	-0.014*	0.079
15	0.686	0.052*	-0.006*	0.070*	-0.015*	0.073
16	0.517*	0.095	0.005*	0.132	-0.010*	0.188

Table 23: Results for Mistral on RTE. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.679	0.152	0.124	0.118	0.111	0.085
1	0.661	0.159	0.119*	0.120	0.102*	0.094
2	0.671	0.158	0.128*	0.121	0.116	0.075
3	0.675	0.161*	0.125	0.124	0.112	0.075
4	0.661	0.173*	0.117*	0.130*	0.098*	0.102
5	0.653*	0.164*	0.114*	0.126*	0.092*	0.108
6	0.668	0.155	0.113*	0.118	0.086*	0.088
7	0.671	0.154	0.117*	0.113	0.091*	0.079
8	0.675	0.157	0.120*	0.112	0.093*	0.078
9	0.661	0.170*	0.117*	0.131	0.091*	0.118
10	0.664	0.198*	0.142*	0.172*	0.124*	0.138
11	0.646*	0.167*	0.118	0.118	0.085*	0.150
12	0.664	0.149	0.115*	0.107	0.082*	0.107
13	0.653	0.095*	0.095*	0.049*	0.055*	0.056
14	0.664	0.142	0.112*	0.099*	0.084*	0.092
15	0.704	0.143	0.153*	0.110	0.117	0.061
16	0.668	0.134	0.116	0.080*	0.060*	0.059

Table 24: Results for Llama-3 on ARC Easy. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.815	0.200	0.126	0.172	0.157	0.076
1	0.814	0.165*	0.153*	0.162	0.162	0.077
2	0.813	0.189	0.136	0.170	0.162	0.078
3	0.814	0.203	0.130	0.181	0.157	0.077
4	0.816	0.203	0.126	0.178	0.156	0.072
5	0.819	0.205	0.124	0.174	0.158	0.069
6	0.817	0.199	0.117	0.174	0.147	0.073
7	0.813	0.199	0.121	0.176	0.147	0.071
8	0.806*	0.197	0.121	0.176	0.150	0.076
9	0.806	0.210	0.137	0.185	0.160	0.077
10	0.798*	0.204	0.129	0.180	0.153	0.080
11	0.790*	0.219*	0.147	0.190*	0.177*	0.084
12	0.781*	0.207	0.132	0.190*	0.165	0.092
13	0.780*	0.196	0.120	0.178	0.152	0.093
14	0.738*	0.179	0.128	0.163	0.156	0.116
15	0.707*	0.157*	0.101	0.143	0.129	0.140
16	0.564*	0.123*	0.070*	0.106*	0.094*	0.232

Table 25: Results for Llama-3 on ARC Challenge. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.513	0.222	0.092	0.202	0.119	0.306
1	0.504	0.209	0.109*	0.191	0.133*	0.313
2	0.503	0.227	0.102	0.202	0.130	0.316
3	0.510	0.220	0.094	0.202	0.121	0.313
4	0.509	0.229	0.102	0.206	0.129	0.313
5	0.509	0.237	0.115	0.217	0.143*	0.304
6	0.508	0.230	0.101	0.207	0.131	0.312
7	0.499	0.237	0.109	0.213	0.145*	0.316
8	0.497	0.239	0.113	0.208	0.148*	0.319
9	0.498	0.234	0.112	0.202	0.145	0.315
10	0.485*	0.229	0.115*	0.196	0.142*	0.325
11	0.474*	0.222	0.109	0.193	0.133	0.332
12	0.475*	0.209	0.100	0.182	0.123	0.328
13	0.495	0.209	0.112	0.194	0.145	0.323
14	0.451*	0.172*	0.090	0.157*	0.108	0.356
15	0.426*	0.187	0.110	0.167*	0.127	0.378
16	0.331*	0.147*	0.085	0.117*	0.101	0.458

Table 26: Results for Llama-3 on OpenBookQA. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.332	0.237	0.139	0.214	0.156	0.473
1	0.338	0.176*	0.193*	0.156*	0.203*	0.467
2	0.340	0.222*	0.164*	0.199*	0.189*	0.466
3	0.340	0.245	0.153	0.223	0.184*	0.465
4	0.346	0.244	0.150*	0.222	0.178*	0.458
5	0.340	0.247	0.154	0.224	0.178	0.461
6	0.350	0.248	0.156	0.224	0.180*	0.449
7	0.354	0.234	0.151	0.214	0.175	0.443
8	0.348	0.235	0.163*	0.215	0.183*	0.452
9	0.354	0.234	0.160*	0.215	0.184*	0.446
10	0.338	0.217*	0.155	0.200*	0.170	0.457
11	0.324	0.202*	0.141	0.188*	0.154	0.466
12	0.310	0.195*	0.136	0.177*	0.159	0.483
13	0.324	0.195*	0.140	0.177*	0.165	0.476
14	0.302	0.174*	0.134	0.163*	0.158	0.486
15	0.288*	0.149*	0.105*	0.140*	0.121*	0.494
16	0.220*	0.111*	0.068*	0.105*	0.086*	0.562

Table 27: Results for Llama-3 on BoolQ. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.821	0.384	0.127	0.272	0.188	0.060
1	0.820	0.088*	0.349*	0.128*	0.313*	0.059
2	0.820	0.272*	0.197*	0.230*	0.224*	0.057
3	0.821	0.369*	0.126	0.284	0.180	0.056
4	0.822	0.342*	0.125	0.266	0.177*	0.062
5	0.818	0.335*	0.122	0.252	0.176*	0.063
6	0.818	0.325*	0.122	0.248*	0.170*	0.059
7	0.822	0.339*	0.123	0.252	0.174*	0.062
8	0.823	0.336*	0.116*	0.247*	0.156*	0.070
9	0.818	0.336*	0.120	0.251*	0.150*	0.065
10	0.818	0.338*	0.129	0.260	0.156*	0.059
11	0.821	0.338*	0.132	0.277	0.163*	0.057
12	0.800*	0.333*	0.123	0.233*	0.155*	0.055
13	0.752*	0.309*	0.098*	0.194*	0.135*	0.032
14	0.762*	0.295*	0.102*	0.199*	0.136*	0.051
15	0.774*	0.372	0.088*	0.268	0.128*	0.065
16	0.807*	0.373	0.110*	0.267	0.158*	0.121

Table 28: Results for Llama-3 on TweetEval. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.520	0.016	0.166	0.079	0.105	0.098
1	0.534*	0.036*	0.179	0.094*	0.122*	0.077
2	0.543*	0.034*	0.175	0.091	0.123*	0.046
3	0.542*	0.035*	0.160	0.089*	0.111*	0.031
4	0.558*	0.032*	0.156	0.087	0.092	0.024
5	0.632*	0.026	0.021*	0.068	-0.024*	0.073
6	0.624*	0.032*	0.071*	0.078	0.025*	0.070
7	0.603*	0.219*	0.192	0.236*	0.163*	0.064
8	0.624*	0.217*	0.191	0.231*	0.165*	0.082
9	0.387*	0.295*	0.267*	0.313*	0.248*	0.304
10	0.423*	0.267*	0.226*	0.293*	0.216*	0.225
11	0.433*	0.214*	0.187	0.241*	0.181*	0.154
12	0.398*	0.247*	0.167	0.268*	0.167*	0.265
13	0.420*	0.284*	0.271*	0.272*	0.187*	0.267
14	0.406*	0.252*	0.194	0.213*	0.147*	0.201
15	0.421*	0.245*	0.204*	0.239*	0.176*	0.209
16	0.350*	0.272*	0.223*	0.241*	0.197*	0.282

Table 29: Results for Llama-3 on Rotten Tomatoes. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.818	0.106	0.093	0.091	0.105	0.201
1	0.811	0.097	0.082	0.087	0.088	0.188
2	0.757*	0.086	0.059*	0.080	0.054*	0.124
3	0.729*	0.091	0.066	0.088	0.054*	0.102
4	0.727*	0.086	0.059*	0.088	0.048*	0.082
5	0.826	0.109	0.110*	0.102*	0.116*	0.201
6	0.814	0.098*	0.110*	0.093	0.112	0.205
7	0.759*	0.105	0.117*	0.100	0.125*	0.147
8	0.792*	0.111	0.104	0.095	0.112	0.189
9	0.732*	0.013*	0.012*	0.012*	0.007*	0.131
10	0.725*	0.009*	0.006*	0.007*	-0.009*	0.100
11	0.787*	0.054*	0.062*	0.060*	0.050*	0.188
12	0.765*	0.081*	0.079	0.088	0.079*	0.176
13	0.555*	0.267*	0.181*	0.251*	0.204*	0.207
14	0.555*	0.249*	0.219*	0.252*	0.231*	0.200
15	0.562*	0.151*	0.170*	0.189*	0.198*	0.191
16	0.531*	0.163*	0.174*	0.208*	0.209*	0.224

Table 30: Results for Llama-3 on SST-2. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.776	0.105	0.097	0.095	0.104	0.158
1	0.819*	0.092*	0.090	0.091	0.086	0.205
2	0.792	0.064*	0.053*	0.075*	0.042*	0.176
3	0.805	0.067*	0.061*	0.080	0.049*	0.189
4	0.799	0.062*	0.051*	0.079*	0.042*	0.187
5	0.685*	0.156*	0.122*	0.121*	0.134*	0.055
6	0.747*	0.110	0.103	0.092	0.102*	0.120
7	0.720*	0.148*	0.132*	0.118*	0.128*	0.086
8	0.763	0.123*	0.107	0.101	0.102	0.148
9	0.778	0.118*	0.099	0.098	0.097	0.171
10	0.818*	0.068*	0.064*	0.070*	0.059*	0.210
11	0.771	0.092	0.082*	0.084	0.072*	0.168
12	0.690*	0.160*	0.135*	0.146*	0.136*	0.058
13	0.507*	0.343*	0.234*	0.251*	0.220*	0.280
14	0.495*	0.334*	0.257*	0.266*	0.253*	0.315
15	0.493*	0.237*	0.217*	0.236*	0.249*	0.339
16	0.491*	0.238*	0.248*	0.278*	0.299*	0.383

Table 31: Results for Llama-3 on RTE. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.697	0.141	0.143	0.144	0.153	0.045
1	0.700	0.078*	0.105*	0.104*	0.116*	0.039
2	0.704	0.112*	0.119*	0.129	0.127*	0.045
3	0.697	0.141	0.131*	0.154*	0.137	0.032
4	0.700	0.135	0.118*	0.139	0.106*	0.092
5	0.700	0.135	0.109*	0.144	0.102*	0.067
6	0.668	0.151	0.102*	0.157*	0.093*	0.079
7	0.661	0.132	0.089*	0.144	0.084*	0.039
8	0.704	0.167*	0.117*	0.164*	0.121*	0.057
9	0.708	0.154	0.136	0.153	0.137*	0.039
10	0.708	0.142	0.132	0.146	0.140*	0.056
11	0.708	0.116*	0.123*	0.123*	0.122*	0.061
12	0.686	0.130	0.108*	0.138	0.120*	0.047
13	0.722	0.172*	0.119*	0.155	0.123*	0.082
14	0.718	0.182*	0.122*	0.166*	0.124*	0.079
15	0.711	0.213*	0.144	0.196*	0.143	0.064
16	0.700	0.224*	0.170*	0.203*	0.166*	0.055

Table 32: Results for Qwen-3 8B on ARC Easy. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.835	0.232	0.155	0.184	0.214	0.106
1	0.838	0.238	0.146	0.180	0.205	0.088
2	0.834	0.233	0.153	0.182	0.207	0.088
3	0.822*	0.221	0.149	0.177	0.203	0.093
4	0.811*	0.234	0.155	0.192	0.199	0.095
5	0.806*	0.245	0.161	0.196	0.204	0.099
6	0.790*	0.248	0.176*	0.206	0.204	0.113
7	0.785*	0.241	0.165	0.202	0.202	0.121
8	0.778*	0.253	0.177	0.214*	0.216	0.122
9	0.769*	0.237	0.172	0.198	0.203	0.132
10	0.753*	0.235	0.184	0.202*	0.211	0.141
11	0.636*	0.171*	0.140	0.139*	0.170*	0.238
12	0.632*	0.211	0.181	0.184	0.207	0.253
13	0.645*	0.209	0.175	0.178	0.203	0.236
14	0.624*	0.176*	0.142	0.148*	0.165*	0.247
15	0.609*	0.175*	0.135*	0.144*	0.164*	0.256
16	0.576*	0.197	0.164	0.164	0.180*	0.293

Table 33: Results for Qwen-3 8B on ARC Challenge. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.558	0.273	0.122	0.189	0.200	0.333
1	0.549	0.273	0.110*	0.183	0.191	0.322
2	0.549	0.277	0.105*	0.185	0.187	0.320
3	0.538*	0.270	0.093*	0.186	0.171*	0.324
4	0.530*	0.268	0.098*	0.192	0.166*	0.331
5	0.536*	0.244	0.101	0.172	0.164*	0.324
6	0.520*	0.250	0.097*	0.183	0.155*	0.337
7	0.498*	0.222*	0.087*	0.158	0.144*	0.353
8	0.497*	0.227*	0.088*	0.168	0.133*	0.354
9	0.500*	0.233*	0.107	0.182	0.138*	0.356
10	0.474*	0.254	0.119	0.194	0.160*	0.384
11	0.405*	0.191*	0.123	0.155	0.152*	0.460
12	0.416*	0.210*	0.142	0.179	0.183	0.450
13	0.414*	0.189*	0.128	0.159	0.163*	0.445
14	0.403*	0.184*	0.135	0.155	0.162*	0.445
15	0.387*	0.187*	0.131	0.148*	0.166*	0.470
16	0.373*	0.183*	0.145	0.156	0.160*	0.485

Table 34: Results for Qwen-3 8B on OpenBookQA. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.312	0.214	0.136	0.188	0.181	0.507
1	0.296	0.213	0.119	0.163*	0.172	0.520
2	0.294	0.213	0.119	0.162*	0.170	0.518
3	0.290	0.199	0.101*	0.149*	0.151	0.518
4	0.288	0.200	0.119	0.157*	0.159	0.518
5	0.274*	0.197	0.112	0.151*	0.149	0.540
6	0.274*	0.200	0.106	0.154*	0.147	0.538
7	0.280*	0.186	0.085*	0.144*	0.127*	0.523
8	0.290	0.171*	0.086*	0.139*	0.129*	0.518
9	0.292	0.175*	0.108	0.144*	0.136*	0.522
10	0.286	0.160*	0.100	0.137*	0.132*	0.533
11	0.264*	0.116*	0.092*	0.116*	0.102*	0.563
12	0.272	0.134*	0.093*	0.124*	0.109*	0.559
13	0.246*	0.138*	0.084*	0.119*	0.100*	0.578
14	0.244*	0.149*	0.097*	0.130*	0.117*	0.590
15	0.250*	0.172*	0.107	0.157*	0.121*	0.588
16	0.242*	0.151*	0.086*	0.131*	0.100*	0.592

Table 35: Results for Qwen-3 8B on BoolQ. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.866	0.603	0.211	0.439	0.343	0.084
1	0.863	0.596	0.151*	0.464*	0.328	0.081
2	0.862	0.574*	0.172*	0.479*	0.321*	0.077
3	0.864	0.553*	0.174*	0.485*	0.308*	0.074
4	0.862	0.545*	0.174*	0.500*	0.301*	0.070
5	0.865	0.572*	0.205	0.500*	0.339	0.083
6	0.861	0.566*	0.211	0.514*	0.319*	0.080
7	0.857*	0.552*	0.216	0.529*	0.323*	0.087
8	0.857*	0.546*	0.232*	0.513*	0.322*	0.080
9	0.859*	0.513*	0.269*	0.470*	0.349	0.071
10	0.860	0.492*	0.298*	0.463*	0.361*	0.070
11	0.814*	0.360*	0.393*	0.398*	0.397*	0.082
12	0.811*	0.410*	0.387*	0.403*	0.389*	0.077
13	0.781*	0.372*	0.327*	0.343*	0.332	0.043
14	0.746*	0.381*	0.318*	0.363*	0.326	0.070
15	0.748*	0.379*	0.319*	0.348*	0.323	0.064
16	0.729*	0.396*	0.323*	0.350*	0.341	0.087

Table 36: Results for Qwen-3 8B on TweetEval. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.656	0.228	0.230	0.218	0.276	0.280
1	0.675*	0.227*	0.204	0.217*	0.218*	0.251
2	0.673*	0.251*	0.274*	0.252*	0.243	0.239
3	0.667*	0.236*	0.272*	0.237*	0.244	0.228
4	0.650	0.300*	0.408*	0.317*	0.316	0.243
5	0.548*	0.350*	0.609*	0.376*	0.546*	0.354
6	0.545*	0.355*	0.619*	0.393*	0.583*	0.366
7	0.588*	0.297*	0.447*	0.318*	0.406*	0.282
8	0.624*	0.173*	0.290*	0.200*	0.237*	0.266
9	0.642	0.104*	0.100*	0.103*	0.112*	0.147
10	0.613*	0.186*	0.231*	0.195	0.219*	0.174
11	0.615*	0.141*	0.135*	0.139*	0.140*	0.210
12	0.636*	0.100*	0.072*	0.099*	0.081*	0.203
13	0.592*	-0.145*	-0.101*	-0.132*	-0.110*	0.208
14	0.584*	-0.028*	0.024*	0.004*	0.030*	0.163
15	0.560*	-0.002*	0.033*	0.001*	0.036*	0.182
16	0.559*	-0.013*	-0.024*	0.027*	0.017*	0.210

Table 37: Results for Qwen-3 8B on Rotten Tomatoes. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.883	0.347	0.367	0.354	0.383	0.090
1	0.873*	0.350	0.376*	0.347	0.380	0.094
2	0.868*	0.334*	0.368	0.337*	0.372	0.097
3	0.850*	0.349	0.353	0.358*	0.352*	0.108
4	0.845*	0.335*	0.376	0.359	0.348*	0.116
5	0.877	0.342	0.360	0.397*	0.354*	0.092
6	0.877	0.351	0.360	0.400*	0.361*	0.094
7	0.871	0.377*	0.344*	0.380*	0.325*	0.087
8	0.879	0.384*	0.339*	0.394*	0.308*	0.073
9	0.853*	0.341	0.258*	0.338	0.254*	0.043
10	0.826*	0.345	0.239*	0.336	0.231*	0.059
11	0.876	0.357	0.329*	0.371	0.332*	0.049
12	0.861	0.323	0.290*	0.323*	0.306*	0.054
13	0.855*	0.310*	0.299*	0.313*	0.309*	0.066
14	0.811*	0.210*	0.211*	0.235*	0.224*	0.039
15	0.825*	0.251*	0.232*	0.260*	0.255*	0.045
16	0.796*	0.262*	0.218*	0.250*	0.243*	0.056

Table 38: Results for Qwen-3 8B on SST-2. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.919	0.354	0.367	0.350	0.367	0.058
1	0.908*	0.355	0.367	0.340*	0.359	0.060
2	0.893*	0.340*	0.353*	0.323*	0.345*	0.061
3	0.860*	0.297*	0.324*	0.298*	0.316*	0.072
4	0.856*	0.298*	0.308*	0.298*	0.303*	0.071
5	0.919	0.367*	0.369	0.372*	0.361	0.062
6	0.916	0.367*	0.363	0.372*	0.361	0.062
7	0.894*	0.338	0.333*	0.344	0.315*	0.050
8	0.913	0.359	0.328*	0.359	0.311*	0.041
9	0.823*	0.315*	0.222*	0.283*	0.237*	0.023
10	0.656*	0.341*	0.179*	0.290*	0.210*	0.203
11	0.664*	0.259*	0.266*	0.266*	0.275*	0.211
12	0.800*	0.310*	0.274*	0.283*	0.285*	0.075
13	0.885*	0.341	0.284*	0.328*	0.301*	0.023
14	0.890*	0.319*	0.262*	0.299*	0.283*	0.017
15	0.882*	0.332*	0.258*	0.313*	0.273*	0.017
16	0.843*	0.280*	0.216*	0.276*	0.232*	0.040

Table 39: Results for Qwen-3 8B on RTE. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.783	0.328	0.321	0.305	0.327	0.187
1	0.780	0.306*	0.316	0.287*	0.328	0.166
2	0.769	0.315	0.311*	0.292	0.324	0.169
3	0.762	0.280*	0.289*	0.289*	0.308*	0.165
4	0.758*	0.276*	0.286*	0.307	0.312*	0.164
5	0.747*	0.291*	0.289*	0.316	0.308*	0.182
6	0.733*	0.295*	0.287*	0.305	0.300*	0.181
7	0.747*	0.251*	0.268*	0.286*	0.281*	0.172
8	0.751*	0.238*	0.260*	0.271*	0.263*	0.161
9	0.783	0.246*	0.240*	0.272*	0.256*	0.127
10	0.798	0.279*	0.257*	0.284*	0.260*	0.102
11	0.794	0.294*	0.324	0.319	0.348*	0.132
12	0.769	0.291*	0.318	0.317	0.344*	0.148
13	0.758	0.241*	0.296*	0.273*	0.313	0.138
14	0.740*	0.217*	0.255*	0.247*	0.274*	0.110
15	0.773	0.242*	0.259*	0.265*	0.285*	0.106
16	0.758	0.251*	0.272*	0.282	0.276*	0.091

Table 40: Results for Qwen-3 4B on ARC Easy. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.805	0.236	0.146	0.204	0.193	0.134
1	0.800	0.233	0.137*	0.194*	0.192	0.138
2	0.795*	0.222*	0.145	0.193	0.194	0.140
3	0.777*	0.196*	0.128	0.169*	0.161	0.150
4	0.765*	0.214	0.130	0.189	0.177	0.156
5	0.770*	0.214	0.146	0.191	0.183	0.157
6	0.760*	0.218	0.135	0.197	0.175	0.159
7	0.752*	0.226	0.152*	0.199	0.183	0.165
8	0.735*	0.208*	0.136	0.186	0.170	0.182
9	0.733*	0.200*	0.150	0.174	0.173	0.165
10	0.712*	0.194*	0.131	0.167	0.151*	0.182
11	0.628*	0.156*	0.125	0.124*	0.133*	0.245
12	0.635*	0.161*	0.126	0.127*	0.146*	0.237
13	0.624*	0.142*	0.117	0.118*	0.135*	0.238
14	0.595*	0.135*	0.127	0.110*	0.140*	0.265
15	0.591*	0.121*	0.107*	0.104*	0.120*	0.263
16	0.542*	0.126*	0.092*	0.106*	0.110*	0.297

Table 41: Results for Qwen-3 4B on ARC Challenge. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.508	0.273	0.126	0.232	0.180	0.391
1	0.507	0.268	0.137*	0.231	0.176	0.394
2	0.497	0.268	0.149*	0.229	0.191	0.397
3	0.491	0.275	0.159*	0.241	0.194	0.397
4	0.477*	0.266	0.161*	0.231	0.190	0.410
5	0.477*	0.264	0.160*	0.239	0.196	0.415
6	0.467*	0.263	0.157*	0.234	0.197*	0.426
7	0.459*	0.259	0.140	0.230	0.177	0.431
8	0.445*	0.239	0.131	0.205	0.169	0.448
9	0.448*	0.244	0.147	0.209	0.179	0.428
10	0.430*	0.241	0.141	0.211	0.176	0.445
11	0.406*	0.199*	0.095	0.168*	0.125*	0.450
12	0.408*	0.214*	0.115	0.180*	0.148	0.452
13	0.404*	0.190*	0.108	0.164*	0.140*	0.444
14	0.381*	0.180*	0.087*	0.153*	0.119*	0.475
15	0.370*	0.190*	0.098	0.151*	0.129*	0.483
16	0.340*	0.149*	0.063*	0.129*	0.083*	0.502

Table 42: Results for Qwen-3 4B on OpenBookQA. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.292	0.206	0.126	0.169	0.149	0.536
1	0.284	0.200	0.124	0.159	0.144	0.546
2	0.276	0.199	0.126	0.161	0.148	0.562
3	0.274	0.185*	0.119	0.157	0.146	0.552
4	0.270	0.191*	0.116	0.163	0.146	0.554
5	0.276	0.194	0.129	0.165	0.156	0.554
6	0.266	0.180*	0.130	0.153	0.152	0.561
7	0.278	0.175*	0.121	0.146*	0.141	0.546
8	0.262	0.163*	0.120	0.134*	0.137	0.564
9	0.258*	0.149*	0.101*	0.123*	0.125	0.556
10	0.242*	0.171*	0.122	0.140	0.150	0.574
11	0.232*	0.144*	0.084*	0.119*	0.109*	0.598
12	0.224*	0.149*	0.077*	0.126*	0.111	0.610
13	0.224*	0.133*	0.066*	0.125*	0.093*	0.597
14	0.232*	0.127*	0.079*	0.113*	0.100*	0.581
15	0.238*	0.113*	0.062*	0.102*	0.076*	0.586
16	0.220*	0.110*	0.050*	0.098*	0.063*	0.587

Table 43: Results for Qwen-3 4B on BoolQ. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.851	0.476	0.248	0.379	0.381	0.105
1	0.851	0.477	0.264*	0.398*	0.380	0.106
2	0.850	0.480	0.285*	0.397	0.402*	0.106
3	0.850	0.465*	0.309*	0.399*	0.398*	0.101
4	0.845	0.420*	0.355*	0.381	0.389*	0.096
5	0.849	0.455*	0.373*	0.394*	0.403*	0.105
6	0.843*	0.441*	0.332*	0.367	0.389	0.101
7	0.838*	0.441*	0.267	0.377	0.353*	0.099
8	0.799*	0.420*	0.251	0.346*	0.302*	0.106
9	0.813*	0.353*	0.169*	0.329*	0.304*	0.057
10	0.800*	0.358*	0.173*	0.342*	0.309*	0.077
11	0.616*	0.201*	0.167*	0.221*	0.177*	0.171
12	0.628*	0.220*	0.147*	0.208*	0.184*	0.143
13	0.661*	0.246*	0.179*	0.242*	0.206*	0.081
14	0.647*	0.181*	0.141*	0.208*	0.168*	0.094
15	0.601*	0.163*	0.128*	0.173*	0.145*	0.117
16	0.537*	0.164*	0.140*	0.186*	0.164*	0.154

Table 44: Results for Qwen-3 4B on TweetEval. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.650	0.180	0.155	0.197	0.172	0.296
1	0.630*	0.269*	0.262*	0.279*	0.255*	0.312
2	0.624*	0.253*	0.286*	0.264*	0.255*	0.310
3	0.597*	0.209*	0.285*	0.235*	0.226*	0.339
4	0.587*	0.225*	0.323*	0.258*	0.261*	0.357
5	0.554*	0.285*	0.300*	0.303*	0.271*	0.399
6	0.616*	0.134*	0.084*	0.140*	0.073*	0.325
7	0.619*	0.099*	0.081*	0.104*	0.084*	0.327
8	0.644	0.083*	0.101*	0.078*	0.117*	0.280
9	0.644	0.078*	0.085*	0.075*	0.080*	0.270
10	0.653	0.088*	0.075*	0.079*	0.060*	0.247
11	0.651	0.146	0.207*	0.151	0.143	0.202
12	0.634	0.041*	-0.008*	0.038*	-0.038*	0.131
13	0.670	0.071*	0.052*	0.042*	0.041*	0.139
14	0.558*	0.075*	-0.006*	0.063*	-0.014*	0.162
15	0.556*	0.056*	-0.002*	0.050*	-0.013*	0.091
16	0.608*	0.071*	0.058*	0.035*	0.042*	0.031

Table 45: Results for Qwen-3 4B on Rotten Tomatoes. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.861	0.437	0.332	0.416	0.345	0.124
1	0.860	0.429*	0.339*	0.419	0.352*	0.125
2	0.856	0.423*	0.349*	0.427	0.357*	0.119
3	0.851*	0.401*	0.333	0.410	0.330	0.112
4	0.842*	0.377*	0.317	0.389*	0.310*	0.112
5	0.849	0.409*	0.331	0.424	0.330	0.129
6	0.852*	0.419*	0.336	0.411	0.333	0.098
7	0.841*	0.359*	0.330	0.363*	0.327	0.094
8	0.734*	0.198*	0.289*	0.214*	0.299*	0.163
9	0.771*	0.242*	0.249*	0.249*	0.254*	0.127
10	0.828*	0.283*	0.284*	0.297*	0.276*	0.094
11	0.797*	0.272*	0.268*	0.264*	0.275*	0.085
12	0.828*	0.272*	0.272*	0.270*	0.278*	0.072
13	0.852	0.294*	0.286*	0.292*	0.297*	0.044
14	0.834*	0.240*	0.256*	0.240*	0.278*	0.036
15	0.811*	0.244*	0.230*	0.231*	0.242*	0.040
16	0.521*	0.272*	0.254*	0.305*	0.292*	0.398

Table 46: Results for Qwen-3 4B on SST-2. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.899	0.391	0.350	0.399	0.354	0.088
1	0.899	0.392	0.354	0.400	0.358	0.085
2	0.900	0.400*	0.353	0.412*	0.353	0.079
3	0.903	0.388	0.352	0.407*	0.336*	0.069
4	0.901	0.376*	0.343	0.387*	0.323*	0.054
5	0.899	0.407*	0.352*	0.419*	0.336*	0.085
6	0.903	0.402	0.294*	0.400	0.329*	0.059
7	0.905	0.413*	0.295*	0.414	0.334	0.064
8	0.884	0.329*	0.298*	0.323*	0.304*	0.037
9	0.892	0.332*	0.230*	0.325*	0.247*	0.030
10	0.900	0.351*	0.246*	0.346*	0.265*	0.034
11	0.890	0.296*	0.299*	0.299*	0.310*	0.029
12	0.900	0.335*	0.328	0.342*	0.341	0.039
13	0.899	0.307*	0.310*	0.323*	0.319*	0.023
14	0.763*	0.204*	0.247*	0.217*	0.256*	0.066
15	0.636*	0.213*	0.223*	0.198*	0.234*	0.205
16	0.509*	0.309*	0.286*	0.320*	0.314*	0.461

Table 47: Results for Qwen-3 4B on RTE. Comp./Suff. denote comprehensiveness/sufficiency; KS denotes Kernel SHAP; orig denotes the unpruned model. Significant changes ($p < 0.05$) are marked with *. Wilcoxon's test is used for Comp./Suff., and McNemar's test for accuracy.

Pruned Layers	Accuracy	Comp. LIME	Suff. LIME	Comp. KS	Suff. KS	ECE
0 (orig)	0.758	0.317	0.308	0.298	0.309	0.191
1	0.758	0.313	0.309	0.299	0.300	0.193
2	0.758	0.300*	0.296	0.291	0.290*	0.202
3	0.758	0.280*	0.303	0.291	0.304	0.176
4	0.758	0.283*	0.319*	0.288	0.329*	0.180
5	0.783	0.303*	0.332*	0.338*	0.331*	0.187
6	0.747	0.301	0.346*	0.325*	0.352*	0.199
7	0.762	0.308	0.340*	0.325*	0.357*	0.181
8	0.758	0.302	0.384*	0.292	0.397*	0.146
9	0.769	0.283*	0.295	0.276	0.330*	0.085
10	0.769	0.276*	0.286	0.259*	0.305	0.073
11	0.715	0.255*	0.255*	0.262*	0.286*	0.102
12	0.697	0.247*	0.241*	0.241*	0.254*	0.090
13	0.697	0.234*	0.240*	0.194*	0.233*	0.051
14	0.610*	0.233*	0.252*	0.192*	0.208*	0.114
15	0.643*	0.214*	0.236*	0.172*	0.186*	0.090
16	0.625*	0.203*	0.240*	0.114*	0.149*	0.099