NormXLogit: The *Head-on-Top* Never Lies

Sina Abbasi¹, Mohammad Reza Modarres¹, Mohammad Taher Pilehvar²

¹Tehran Institute for Advanced Studies, Khatam University, Iran ²Cardiff University, United Kingdom s.abbasi401@khatam.ac.ir, m.modares401@khatam.ac.ir, pilehvarmt@cardiff.ac.uk

Abstract

The Transformer architecture has emerged as the dominant choice for building large language models (LLMs). However, with new LLMs emerging on a frequent basis, it is important to consider the potential value of architecture-agnostic approaches that can provide interpretability across a variety of architectures. Despite recent successes in the interpretability of LLMs, many existing approaches rely on complex methods that are often tied to a specific model design and come with a significant computational cost. To address these limitations, we propose a novel technique, called NormXLogit, for assessing the significance of individual input tokens. This method operates based on the input and output representations associated with each token. First, we demonstrate that during the pre-training of LLMs, the norms of word embeddings capture the importance of input tokens. Second, we reveal a significant relationship between a token's importance and the extent to which its representation can resemble the model's final prediction. Through extensive analysis, we show that our approach consistently outperforms existing gradient-based methods in terms of faithfulness. Additionally, our method achieves better performance in layer-wise explanations compared to the most prominent architecturespecific methods.

1 Introduction

Transformer-based models have gained widespread adoption across various natural language processing (NLP) tasks, demonstrating their versatility. However, the underlying mechanisms of these models are not quite understood. This means when the model fails and generates inaccurate, toxic, or harmful content, we are unable to diagnose the source and improve the model's behavior. Consequently, a multitude of endeavors in recent years aimed at enhancing the interpretability of these models (Kobayashi et al. 2021; Modarressi et al. 2023; Mohebbi et al. 2023).

Architecture-agnostic methods like perturbation-based and gradient-based techniques are commonly used to identify important input tokens influencing a model's predictions. In perturbation-based methods, one can simply erase the input tokens one at a time to observe their impact on the model's output (Li, Monroe, and Jurafsky 2017). However, a common limitation of these methods is that they can



Figure 1: (a) Importance scores of NormXLogit for the sentiment analysis task. NormXLogit generates attributions perlabel with signed scores denoting positive/negative impact. (b) Applying the head-on-top (HoT) on each of the final representations to obtain a prediction based on each token.

inadvertently create out-of-distribution and nonsensical inputs, which can lead to misleading results. In another direction, the main idea behind the gradient-based methods is to compute the derivative of the output with respect to input tokens to find their importance (Li et al. 2016). While gradient-based methods have been shown to be more faithful than perturbation-based methods, Wang et al. (2020) has demonstrated that they are easily manipulable and may not provide reliable interpretations.

By leveraging the internal components of the target model, a new class of architecture-specific approaches, termed vector-based methods, has been developed to decompose each token into its constituent representations (Kobayashi et al. 2021; Ferrando, Gállego, and Costa-jussà 2022). Most of these approaches offer per-layer explanations, which are subsequently aggregated using the *rollout* technique (Abnar and Zuidema 2020) to achieve a global interpretation that integrates all layers of the model. However, this method of aggregation can result in inaccurate outcomes due to the vanishing attribution problem (Mehri et al. 2024). Despite recent advancements in faithfulness, a key drawback of vector-based methods is their architecture-specific design,

Preprint. Under review.

which limits their adaptability to the rapidly evolving landscape of LLMs. Furthermore, almost all of these methods ignore the *head-on-top*¹ which is crucial to produce taskdependent explanations.

While these methods have made significant strides, additional challenges have emerged. Improvements to these techniques often come with considerable computational costs. In perturbation-based methods, it is costly to search for appropriate combinations of tokens to intervene, as this requires multiple forward passes and adjustments to the input. Similarly, in advanced gradient-based methods like Integrated Gradients (Sundararajan, Taly, and Yan 2017) and Smooth-Grad (Smilkov et al. 2017), attributions are computed by iteratively applying backpropagation. This approach can incur substantial computational overhead due to the repeated forward and backward passes required.

In response to these limitations, this paper presents NormXLogit, a simple yet powerful, architecture-agnostic approach that outperforms many of the sophisticated techniques. NormXLogit does not depend on any specific architecture and could be easily applied to any NLP task. This method leverages the rich semantic and syntactic information encoded in the final layer representations of the model, in conjunction with the norm of input embeddings, resembling an end-to-end interpretation that eliminates the need for any aggregation method, such as rollout. Motivated by DecompX (Modarressi et al. 2023), we incorporate the headon-top of pre-trained models into our analysis to obtain importance scores with respect to the task. We posit that the head-on-top of the pre-trained language models serves as a task-specific interpreter of token attribution², tailoring its attention to the nuances of the task at hand. This helps NormXLogit to generate per-label attributions with positive and negative impacts of each input token (Figure 1(a)). In addition, our method eliminates the need for any backward passes, utilizing the pre-trained model only once to generate the contextualized representation of each token, which significantly reduces the computational cost compared to other methods.

NormXLogit is characterized by combining the informativeness of input embeddings with the interpretation provided by the head-on-top. Based on comprehensive evaluation across various tasks and models, we demonstrate that in numerous instances, the faithfulness of this method surpasses that of widely recognized gradient-based approaches. Moreover, in regression setups where a classification head is absent, our method demonstrates superior performance compared to architecture-specific methods. Additionally, to evaluate layer-wise explanations, we conduct experiments on various linguistic phenomena to assess the model's ability to differentiate between grammatically correct and incorrect sentences. Our results indicate that, in most scenarios, our proposed method performs better than or is competitive with other approaches.

2 Related Work

In recent years, vector-based analysis of Transformers has emerged as an architecture-specific approach. The motivation behind these methods stems from the observation that attention weights can be misleading for interpretability purposes (Jain and Wallace 2019; Serrano and Smith 2019). Kobayashi et al. (2021) extended the Transformer's components for analysis by capturing the whole attention block, rather than relying solely on attention weights. In order to aggregate the per-layer attributions of previous methods to obtain a global attribution, Abnar and Zuidema (2020) proposed two different approaches to quantify the flow of information through self-attention; *attention rollout* and *attention flow*.

GlobEnc (Modarressi et al. 2022) and ALTI (Ferrando, Gállego, and Costa-jussà 2022) tried to improve previous work by further decomposing other components in the Transformer layers and aggregating them using attention rollout. ALTI questioned the way Kobayashi et al. (2021) interprets the contribution of each decomposed vector using its ℓ^2 norm. They suggested that Manhattan distance can vield better results due to the properties of the representation space. At the local level, GlobEnc expands the scope of components beyond the attention block. They ignored the impact of the feed-froward network on the contribution of each token and tried to approximate it by adding the second residual connection and layer normalization into the analysis. In order to capture the influence of the feed-forward network, Modarressi et al. (2023) proposed DecompX. DecompX solved the problems of using rollout by propagating decomposed vectors through different layers of the Transformer. DecompX approximated and decomposed the activation function which led to a better attribution score according to their experiments. They also incorporated the classification head into the analysis which caused per-label explanations.

Perturbation-based methods typically involve perturbing or erasing parts of the input to investigate the causal relationship between input features and the model's final prediction. This category of interpretability methods includes well-known approaches such as SHAP (Lundberg and Lee 2017) and LIME (Ribeiro, Singh, and Guestrin 2016). Recently, Mohebbi et al. (2023) proposed *Value Zeroing* which is based on the Explaining-by-Removing intuition (Covert, Lundberg, and Lee 2022), in order to quantify the context mixing. Their approach, in contrast to other perturbationbased methods, does not remove the input token representations. Value Zeroing instead suggests zeroing the value vector of each token to measure its contribution.

Gradient-based methods involve analyzing the gradients of the model's output with respect to the input features to understand their impact on the model's decision-making process. Methods such as Gradient Norm (Simonyan, Vedaldi, and Zisserman 2014), Gradient×Input (Kindermans et al. 2016), and Integrated Gradients (Sundararajan, Taly, and Yan 2017) are the most prominent ones in this category. However, the trustworthiness of gradient-based models has indeed been a subject of scrutiny and questioning (Adebayo et al. 2020).

¹By 'head-on-top', we are referring to the classification or regression head used on top of the pre-trained models.

²We use 'attribution' and 'importance' interchangeably.

3 Proposed Approach

3.1 Background: Transformer Architecture

Transformers are built upon an encoder-decoder structure, where the encoder and decoder components consist of multiple identical layers stacked on top of each other. In this section, we offer a concise overview of the operations carried out within an encoder layer.

An encoder layer of the Transformer architecture incorporates two sub-layers. A multi-head self-attention block (MHA) and a position-wise fully connected feed-forward network (FFN), each followed by a residual connection (RES) and layer normalization (LN). The output of each sub-layer is:

$$LN(X^{l} + Sublayer(X^{l}))$$
(1)

where $X^l = (x_1^l, x_2^l, ..., x_n^l)$, $x_i^l \in \mathbb{R}^{d_{model}}$ is the *i*-th input representation in layer l, and Sublayer (X^l) shows the functionality applied by each one of the sublayers to X^l .

MHA. This component is responsible for creating contextualized representations for the input elements. The output representation of MHA for token x_i and head h in l-th layer is then calculated as the weighted sum of transformed input representations:

$$\tilde{x}_{i}^{l\left(\stackrel{\frown}{\mathbf{b}}\right)} = \sum_{j=1}^{n} \alpha_{i,j}^{l\left(\stackrel{\frown}{\mathbf{b}}\right)} v_{j}^{l\left(\stackrel{\frown}{\mathbf{b}}\right)} \tag{2}$$

where $\alpha_{i,j}^{l(\mathbf{h})}$ represents the attention weight of token *i* with respect to token *j* in the *h*-th head of the MHA of the *l*-th layer. Then, in order to aggregate the outputs of all heads:

$$\tilde{x}_i^l = \operatorname{Concat}(\tilde{x}_i^{l(1)}, \tilde{x}_i^{l(2)}, ..., \tilde{x}_i^{l(H)}) W_O^l + b_o^l \qquad (3)$$

where H is the number of attention heads, $W_O^l \in \mathbb{R}^{d_{model} \times d_{model}}$ is the weight matrix, and $b_O^l \in \mathbb{R}^{d_{model}}$ is the bias vector of the final projection for the *l*-th layer.

RES and LN. The RES takes the input and output of the MHA and adds them together which is followed by the LN:

$$\tilde{x}_i^l \leftarrow \mathrm{LN}(x_i^l + \tilde{x}_i^l) \tag{4}$$

FFN. The output of the first LN is passed through the FFN, which applies two linear transformations to it with a ReLU activation function in between. The input and output dimension of FFN is equal to d_{model} . Then similarly, the output of the FFN passes through another LN and undergoes a RES:

$$\tilde{z}_i^l = \max(0, \tilde{x}_i^l W_1^l + b_1^l) W_2^l + b_2^l \tag{5}$$

$$z_i^l \leftarrow \mathrm{LN}(z_i^l + \tilde{z}_i^l) \tag{6}$$

The $W_{\{1,2\}}^l$ and $b_{\{1,2\}}^l$ are the parameters corresponding to the first and second linear transformations of the *l*-th layer.

Kobayashi et al. (2021) demonstrated that the output representation of each token produced by the attention block can be explained via two effects: (i) "preserving" its original input using the RES and the contribution of the token itself through context mixing of MHA, and (ii) "mixing" the representations in the context (except the target token). They showed that the preserving effect is predominant, primarily due to the higher contribution of RES to the output representation.

3.2 Norm of Word Embedding

Oyama, Yokoi, and Shimodaira (2023) demonstrated that the norm of input embeddings encodes information gain. They showed that tokens with higher ℓ^2 norm carry more information, effectively capturing the least frequent words in the text. Additionally, based on the Eq. 2, the MHA could be interpreted as the weighted sum of transformed vectors. In other words, the final representation of each token is built by mixing the representations of all tokens in the input sequence. Consequently, tokens with higher norms are expected to contribute more to the final representation of the target token. Higher contribution suggests greater importance, allowing us to utilize the ℓ^2 norm of word embeddings to identify crucial tokens influencing the model's decision.

3.3 LogAt: Logit Attribution

The tasks in the domain of NLP can be broadly divided into two main categories: classification tasks and regression tasks. For both of these setups, we utilize a special token (often known as [CLS]³), which is embedded in almost all pre-trained models. This token serves as a single vector representing the entire input sequence, which is then fed into head-on-top, an FFN placed on top of the pre-trained model to produce the output prediction.

The intuition behind the attention mechanism implies that more important tokens have a greater contribution to building the final representation of the [CLS] token. In other words, an identical [CLS] embedding is fed into the model for all input sequences, and based on the fine-tuning objective, the attention block attempts to utilize the most relevant (i.e., important) tokens to construct the new representation of [CLS]. This suggests that the [CLS] token has a higher degree of similarity to the most important input tokens in the model's decision-making process. To identify the tokens that are most similar to [CLS], we use the head-on-top to evaluate how each individual token in the input contributes to predicting the target task. In the following, we describe the approach for each setup.

Classification. In a classification setup, the output of the head-on-top for each sample is a vector of length equal to the number of labels (i.e., classes). The values in this output vector are referred to as logits, which are further processed using the softmax function to obtain probabilities over the output labels. The model's final prediction is the label associated with the highest logit value. To determine the most important input tokens for a model with L layers, we apply the head-on-top to each one of the output representations at layer L, as illustrated in Figure 1(b). Next, we extract the logits corresponding to the predicted class, which is already determined by applying the head-on-top to the [CLS] token.

³The name of this special token may vary depending on the model. Also, in auto-regressive models, the last token in the input is typically used for classification.

The logit value associated with each token represents its attribution, and tokens with the highest logits are regarded as the most important for the classification task. We call this method Logit Attribution (LogAt). To calculate the attribution (Att_{LogAt}) of the token *i* for a task with *C* classes and a classification head HoT_{clas}(\cdot) $\in \mathbb{R}^C$, we have:

$$\operatorname{Att}_{\operatorname{LogAt}}(x_i) = \operatorname{HoT}_{\operatorname{clas}}(x_i^L)[\hat{p}]$$
(7)

where x_i^L is the final representation of the *i*-th token in a model with L layers, and $\hat{p} \in \{0, 1, ..., C - 1\}$ denotes the index of the predicted class. By changing the index of \hat{p} to other class labels in the task, we can identify the important tokens relative to those classes as well, leading to a per-label attribution technique.

Due to the dominance of the "preserving" effect in the attention block, the contextualized representations in the last layer still retain the identity of the original input tokens. As a result, the logits can be seen as a direct reflection of each token's contribution. The use of the head-on-top provides task-specific explanations, allowing us to semantically identify the tokens that are most critical for the target task. Furthermore, the sign of the logits provides insight into the direction of the contributions, indicating whether each label is positively or negatively influenced, specifically with respect to the model's predicted label.

To interpret the choice of token in various language modeling objectives, we categorize them as classification tasks, where the number of labels corresponds to the vocabulary size. In language modeling, the goal is to predict the correct word given the context, which yields a probability distribution over the vocabulary for generating each individual word. In this setup, we utilize the masked language modeling head as the head-on-top to identify the tokens that contribute most to predicting the [Mask] token.

Regression. For the regression setup, the approach typically involves generating a single value in the output rather than a vector of probabilities. So, instead of taking the largest logit corresponding to the prediction label, we take the absolute distance of the output for each token from the model's prediction. For the attribution of i-th token in a regression task, we have:

$$\operatorname{Att}_{\operatorname{LogAt}}(x_i) = \left| \operatorname{HoT}_{\operatorname{reg}}(x_i^L) - \operatorname{HoT}_{\operatorname{reg}}([\operatorname{CLS}]^L) \right| \qquad (8)$$

where $\operatorname{HoT}_{\operatorname{reg}}(\cdot) \in \mathbb{R}$ denotes the regression head, x_i^L is the final representation of the *i*-th token in a model with L layers, and $[\operatorname{CLS}]^L$ is the final representation of the $[\operatorname{CLS}]$ token.

3.4 NormXLogit

Although LogAt provides valuable explanations of the model's decision-making process, our experiments show that considering the informativeness of the norm of word embeddings can yield more faithful results. Therefore, we introduce NormXLogit, an architecture-agnostic interpretation method that can be applied to any task and domain. The attribution of token *i* using NormXLogit is obtained as:

$$\operatorname{Att}_{\operatorname{Norm}\operatorname{XLogit}}(x_i) = \left\|x_i^0\right\|_2 \times \operatorname{Att}_{\operatorname{LogAt}}(x_i) \tag{9}$$

where the $||x_i^0||_2$ is the ℓ^2 norm of the input word embedding for the *i*-th token, and $\operatorname{Att}_{\operatorname{LogAt}}(\cdot)$ is the LogAt attribution according to the task setup.

4 Experiment 1: Faithfulness Analysis

4.1 Experimental Setup

To analyze the faithfulness of NormXLogit we conduct our first experiment on classic classification and regression tasks.

Data. In the classification setup, we will use SST-2 (Socher et al. 2013) for sentiment analysis and MultiNLI (Williams, Nangia, and Bowman 2018) for recognizing textual entailment. SST-2 contains sentences with negative and positive labels extracted from movie reviews, while MultiNLI includes sentence pairs labeled as entailment, contradiction, and neutral. Additionally, we employ STS-B (Cer et al. 2017) to evaluate semantic textual similarity as a regression task. This dataset provides a benchmark for measuring the similarity between sentence pairs, with annotations ranging from 0 (no similarity) to 5 (semantic equivalence).

Models. Our target models in this section involve three prominent models: LLAMA 2 (Touvron et al. 2023), De-BERTa (He, Gao, and Chen 2023), and BERT (Devlin et al. 2019).⁴ We use the fine-tuned version of each model for the corresponding task. To fine-tune LLAMA 2 and perform inference, we employ the LoRA (Hu et al. 2021) technique with a rank of 4 from the PEFT library⁵.

Input Attribution Methods. To analyze the performance of our proposed method, we compare NormXLogit with three well-known gradient-based input attribution methods: Gradient Norm, Gradient×Input, and Integrated Gradients. For all of these methods, we use the ℓ^1 norm as the aggregation approach. To account for vector-based approaches, we adopt DecompX as the current state-of-the-art method among them. However, this family of methods is primarily developed for BERT-like architectures and may not be applicable to all models. In addition, we consider a random baseline where tokens are ranked randomly from most important to least important.

Evaluation Metrics. To assess the faithfulness of the aforementioned methods, we utilize two metrics: AOPC (Samek et al. 2015) for classification tasks and Accuracy for regression setups.

AOPC: This metric involves perturbing K% of the most important tokens in the input sequence and observing the resulting changes in the model's predictions. For the masked language modeling objectives, masking is used for token perturbations, while for auto-regressive models, deletions are employed due to the absence of a [MASK] token. For a

⁴Specifically, we employ the 7 billion parameter variant of LLAMA 2, the uncased BERT_{base} model, and DeBERTaV3_{base}, all of which are obtained from HuggingFace's Transformers library (Wolf et al. 2020).

⁵https://github.com/huggingface/peft

	SS	Г-2 (АОРС ⁻	†)	MN	LI (AOPC	†)	STS-B (Acc↓)			
	LLAMA 2	DeBERTa	BERT	LLAMA 2	DeBERTa	BERT	LLAMA 2	DeBERTa	BERT	
Random Baseline	0.256	0.266	0.245	0.421	0.445	0.361	0.283	0.430	0.457	
Gradient Norm	0.216	0.320	0.331	0.419	0.535	0.460	0.351	0.338	0.374	
Gradient×Input	0.236	0.345	0.339	0.442	0.565	0.456	0.255	0.214	0.358	
Integrated Gradients	0.220	0.346	0.367	0.448	0.571	0.466	0.237	0.227	0.370	
DecompX	N/A	N/A	0.574	N/A	N/A	0.585	N/A	N/A	0.336	
ℓ^2 norm	0.299	0.360	0.311	0.420	0.473	0.393	0.251	0.199	0.321	
LogAt	0.341	0.377	0.364	0.518	0.548	0.566	0.167	0.423	0.313	
NormXLogit	0.341	0.386	0.423	0.519	0.566	0.556	0.233	0.320	0.281	

Table 1: Performance evaluation of NormXLogit against other methods across various model and dataset configurations. Each value is computed by averaging across all perturbation ratios (higher AOPC and lower Accuracy are better).



Figure 2: AOPC of different attribution methods for LLAMA 2 fine-tuned on SST-2 (higher AOPC is better).

given input sequence X_i , the perturbed sequence $X_i \setminus K$ is generated by applying the perturbation on K% of the most important tokens. Then for all of the instances in the dataset, the average AOPC is defined as:

AOPC(K\%) =
$$\frac{1}{m} \sum_{i=1}^{m} [f_{\hat{y}}(X_i) - f_{\hat{y}}(X_i \setminus K)]$$
 (10)

where *m* is the number of instances, and $f_{\hat{y}}(X)$ is the model's output probability for label \hat{y} . A higher AOPC indicates that the model exhibits a larger drop in probability for the predicted class, reflecting greater sensitivity to perturbated tokens.

Accuracy: This metric operates by observing the accuracy drop when perturbing different proportions of the most important tokens in the input. For regression tasks, we utilized the Pearson correlation coefficient as the accuracy metric. For the Accuracy, lower values indicate better performance.

4.2 Results

Figure 2 illustrates the superior performance of NormXLogit in LLAMA 2 fine-tuned on SST-2. NormXLogit achieves higher AOPC scores across all thresholds, indicating its



Figure 3: Accuracy of different attribution methods for BERT fine-tuned on STS-B (lower Accuracy is better).

effectiveness in identifying crucial tokens for the model's decision-making process. It should be noted that DecompX, due to its architecture-specific nature, may not be applicable to LLAMA 2. Additionally, even if it were, the computational cost of DecompX may not be easily manageable given the size of LLAMA 2 on many accessible hardware configurations.

In the regression setup of STS-B depicted in Figure 3, dropping important tokens results in a decrease in Accuracy. To leverage DecompX for this setup, in the absence of a classification head, we applied the ℓ^2 norm to the decomposed vectors obtained from the final layer. The results for the initial K% ratios are very close, with DecompX and Gradient×Input showing a slight lead at the outset. However, after dropping 40% of the most important tokens, the performance of all these methods deteriorates, while NormXLogit continues to experience a drop in Accuracy.

Table 1 presents the average AOPC and Accuracy across different ratios of perturbation, evaluated on various models and datasets⁶. In SST-2, NormXLogit consistently outper-

⁶The corresponding diagrams are also provided in the Appendix.

Phenomenon	UID	Example (Target ✔/Foil ★)
Anaphor Number Agreement	ana	$\underline{\text{This government}} \text{ alarms itself } \checkmark / \text{themselves } \bigstar.$
Determiner-Noun Agreement	dna dnaa	Russell explored this ✔/these ★ <u>mall</u> . Patients scan this ✔/these ★ orange <u>brochure</u> .
Subject-Verb Agreement	darn rpsv	The <u>sister</u> of doctors writes \checkmark /write \checkmark . The <u>pedestrian</u> has \checkmark /have \checkmark forgotten Grace.

Table 2: Examples of various linguistic phenomena that have been investigated in our experiments. Each paradigm is represented by a unique identifier (UID) from the BLIMP dataset. The target and foil words are denoted using check and cross marks. In each instance, the relevant evidence is <u>underlined</u>.

forms architecture-agnostic methods. However, DecompX, which is specific to the BERT architecture, results in a higher drop in AOPC. In the MultiNLI dataset, NormXLogit performs better than gradient-based approaches in LLAMA 2 and BERT, though Integrated Gradients show a slight edge in the DeBERTa model. In the BERT model, similar to SST-2, DecompX performs better but the difference is notably smaller compared to the SST-2 dataset.

In the regression setup, surprisingly, the ℓ^2 norm outperforms other methods and also helps Gradient×Input achieve better results. In the BERT model, the absence of a classification head diminishes DecompX's effectiveness, resulting in performance worse than that of the input embeddings' norms. In LLAMA 2, NormXLogit slightly surpasses all gradient-based methods, largely due to the strong performance of LogAt.

5 Experiment 2: Evidence Alignment

5.1 Experimental Setup

In this section, we focus on per-layer interpretations provided by different methods rather than their global attributions. Specifically, we concentrate on the masked language modeling objective and look for tokens that have the highest impact on the predicted token.

Data. To assess the target model's sensitivity to linguistic phenomena, we employ the BLIMP dataset (Warstadt et al. 2020) which contains sentence pairs with minimal contrasts in syntax, morphology, or semantics. The dataset is constructed to provide samples where the true label is uniquely determined by a single word in each sentence. This word, which serves as the decisive factor in determining grammatical acceptability, is termed the *evidence*. Following Mohebbi et al. (2023), we utilize a subset of the BLIMP dataset, comprising 5 paradigms that represent 3 distinct linguistic phenomena. An example of each phenomenon has been provided in Table 2.

Using spaCy (Honnibal and Montani 2017), we are able to identify the evidence of each linguistic phenomenon. For *anaphor number agreement*, we employ NeuralCoref⁷ to detect the coreferent of the target word. To address *determinernoun agreement*, we generate the dependency tree for each sample and extract the determiners corresponding to the target noun. Lastly, for *subject-verb agreement*, the same dependency tree can be used to identify the subjects associated with the verb.

Model. In this section, we employ the RoBERTa (Liu et al. 2019) model for our evaluations. We use both pre-trained⁸ and fine-tuned versions of the model. For fine-tuning, the target token is replaced with [MASK], and the model is optimized to select the correct target token (the grammatically appropriate word) over the foil token (a similar but grammatically incorrect alternative). Next, for inference, we use the head-on-top, also known as the unembedding matrix, to generate probabilities over the vocabulary.

Attribution Methods. GlobEnc, ALTI, and Value Zeroing are the attribution methods we consider for comparison in this experiment. Unlike Value Zeroing, which focuses on layer-wise attributions, the other two methods generate global importance scores. To acquire per-layer explanations for GlobEnc and ALTI, we bypass the rollout aggregation method to directly derive per-layer scores and we denote them as GlobEnc¬ and ALTI¬. Moreover, for NormXLogit, to obtain the attributions of layer l we use the LogAt on the output representations of *l*-th layer in combination with the ℓ^2 norm of the input embeddings where $l \in \{1, 2, ..., L\}$. In this language modeling setup, applying the head-on-top method to the final representations of tokens in the sequence provides a probability distribution over the vocabulary for each input token. Then, LogAt(target) is the probability assigned to the target token for each input token, which is considered its attribution score. Using the per-label explanations that could be obtained via LogAt, we also demonstrate the importance of evidence words in predicting both foil and target tokens. These explanations can be generated for any word in the vocabulary, as illustrated in the Appendix. We also consider a random baseline in which tokens attributed equal scores.

Alignment Metrics. Following Yin and Neubig (2022), we define the known evidence as a binary vector \mathcal{E} with a length equal to the input sequence X. In this vector, a value of 1 at a given index indicates the presence of known evidence, while a value of 0 indicates its absence. Similarly, the explanation \mathcal{S} is also represented as a vector of the same length, where the *i*-th element of it S_i , shows the score produced by an attribution method for predicting the target token. To evaluate the alignment between evidence and explanation vectors, we take advantage of Dot Product and Average Precision metrics.

Dot Product: The dot product $\mathcal{E} \cdot \mathcal{S}$ computes the total score that the target attribution method assigns to the known evidence.

Average Precision: To evaluate whether an attribution method has found the most important tokens in the input sequence, we use Average Precision. This metric concentrates on the ranking obtained via the attribution method rather

⁷https://github.com/huggingface/neuralcoref

⁸The results of the pre-trained model are covered in the Appendix.



Figure 4: Per-layer alignment between evidence and explanation vectors for the fine-tuned version of RoBERTa, calculated using Dot Product metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.14.

than its scores. To calculate the Average Precision for a single sample, we have:

$$AP = \sum_{k=1}^{n} (R_k - R_{k-1}) P_k$$
(11)

where R_k and P_k indicate the recall and precision at threshold k, and n is the length of input sequence.

5.2 Results

Figures 4 and 5 present the results of the alignment for different attribution methods and the known evidence enforcing a linguistic paradigm. In Figure 4, it can be seen that across almost all layers, NormXLogit consistently outperforms other methods in the experiment. The LogAt scores corresponding to the foil token in both alignment metrics are lower than those obtained from the target token. Specifically, as we progress to higher Transformer layers, there is a drop in alignment for the foil token and an increase for the target token. This pattern can be explained by the fact that token representations become more contextualized as they pass through layers. Increased context mixing from evidence words can lead to a correct prediction (LogAt(Target)), while reduced context mixing can result in incorrect predictions (LogAt(Foil)).

As noted earlier, the LogAt scores can be calculated for other tokens in the vocabulary as well. Our analysis shows that the LogAt score for the word 'plural' (LogAt("plural")) outperforms all other methods in our experiments by a notable margin. This superior performance, unlike that of other random words, might be attributed to the *number agreement* phenomena underlying

12	0.28	0.23	0.33	0.22	0.32	0.31	0.35	0.33	- (0.40
11	0.30	0.36	0.40	0.36	0.17	0.31	0.36	0.36		
10	0.30	0.27	0.33	0.29	0.20	0.28	0.35	0.35	- (0.35
6	0.29	0.37	0.40	0.38	0.21	0.30	0.36	0.36		
00	0.29	0.29	0.30	0.31	0.21	0.31	0.36	0.36		
۹۲ ۲	0.29	0.28	0.35	0.30	0.19	0.30	0.36	0.35	- (0.30
6 6	0.28	0.32	0.33	0.34	0.19	0.33	0.38	0.38		
ŝ	0.30	0.31	0.33	0.31	0.17	0.33	0.35	0.35	- (0.25
4	0.28		0.31		0.17	0.35	0.36	0.36		
m	0.30	0.37	0.38	0.37	0.17	0.34	0.35	0.35		
2	0.29	0.34	0.38	0.35	0.17	0.33	0.31	0.31	- (0.20
г	0.29	0.29	0.25	0.33	0.17	0.35	0.35	0.36		
	Random Baseline	GlobEnc.,	ALTI-	Value Zeroing	I2 norm	LogAt(Foil)	LogAt(Target)	NormXLogit		

Figure 5: Per-layer alignment between evidence and explanation vectors for the fine-tuned version of RoBERTa, calculated using Average Precision metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.35.

this experiment. At layer 7, the results of LogAt("plural") for Dot Product and Average Precision are 0.28 and 0.50, respectively (refer to Appendix for complete results).

As mentioned in the caption of Figures 4 and 5, the high alignment between the norm of input word embeddings and the evidence confirms that indeed they are informative.

6 Conclusion and Future Work

In this paper, we introduced NormXLogit, an architectureagnostic interpretation method that can be applied to any setup to reveal the opaque mechanism behind the decisionmaking process of LLMs. This method is fast and scalable, and it can be applied to models of any size. By utilizing the head-on-top, we gain the advantage of producing per-label explanations, which can be used to identify the most important tokens with respect to each label. Through extensive experiments, we showed that the attributions produced by NormXLogit are not only more faithful than those generated by gradient-based methods but also competitive with architecture-specific approaches.

Future work could explore the applicability of our proposed method to other domains and models, such as vision and non-Transformer architectures. Another promising direction is to investigate how aggregating attributions across all labels in a classification setup could lead to improved explanations.

References

Abnar, S.; and Zuidema, W. 2020. Quantifying Attention Flow in Transformers. In Jurafsky, D.; Chai, J.; Schluter, N.; and Tetreault, J., eds., *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4190– 4197. Online: Association for Computational Linguistics.

Adebayo, J.; Gilmer, J.; Muelly, M.; Goodfellow, I.; Hardt, M.; and Kim, B. 2020. Sanity Checks for Saliency Maps. arXiv:1810.03292.

Cer, D.; Diab, M.; Agirre, E.; Lopez-Gazpio, I.; and Specia, L. 2017. SemEval-2017 Task 1: Semantic Textual Similarity Multilingual and Crosslingual Focused Evaluation. In Bethard, S.; Carpuat, M.; Apidianaki, M.; Mohammad, S. M.; Cer, D.; and Jurgens, D., eds., *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-*2017), 1–14. Vancouver, Canada: Association for Computational Linguistics.

Covert, I.; Lundberg, S.; and Lee, S.-I. 2022. Explaining by Removing: A Unified Framework for Model Explanation. arXiv:2011.14878.

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Burstein, J.; Doran, C.; and Solorio, T., eds., *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 4171–4186. Minneapolis, Minnesota: Association for Computational Linguistics.

Ferrando, J.; Gállego, G. I.; and Costa-jussà, M. R. 2022. Measuring the Mixing of Contextual Information in the Transformer. In Goldberg, Y.; Kozareva, Z.; and Zhang, Y., eds., *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, 8698–8714. Abu Dhabi, United Arab Emirates: Association for Computational Linguistics.

He, P.; Gao, J.; and Chen, W. 2023. DeBER-TaV3: Improving DeBERTa using ELECTRA-Style Pre-Training with Gradient-Disentangled Embedding Sharing. arXiv:2111.09543.

Honnibal, M.; and Montani, I. 2017. spaCy 2: Natural language understanding with Bloom embeddings, convolutional neural networks and incremental parsing. To appear.

Hu, E. J.; Shen, Y.; Wallis, P.; Allen-Zhu, Z.; Li, Y.; Wang, S.; Wang, L.; and Chen, W. 2021. LoRA: Low-Rank Adaptation of Large Language Models. arXiv:2106.09685.

Jain, S.; and Wallace, B. C. 2019. Attention is not Explanation. In Burstein, J.; Doran, C.; and Solorio, T., eds., *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 3543–3556. Minneapolis, Minnesota: Association for Computational Linguistics.

Kindermans, P.-J.; Schütt, K.; Müller, K.-R.; and Dähne, S. 2016. Investigating the influence of noise and distractors on the interpretation of neural networks. arXiv:1611.07270.

Kobayashi, G.; Kuribayashi, T.; Yokoi, S.; and Inui, K. 2021. Incorporating Residual and Normalization Layers into Analysis of Masked Language Models. In Moens, M.-F.; Huang, X.; Specia, L.; and Yih, S. W.-t., eds., *Proceedings of the* 2021 Conference on Empirical Methods in Natural Language Processing, 4547–4568. Online and Punta Cana, Dominican Republic: Association for Computational Linguistics.

Li, J.; Chen, X.; Hovy, E.; and Jurafsky, D. 2016. Visualizing and Understanding Neural Models in NLP. In Knight, K.; Nenkova, A.; and Rambow, O., eds., *Proceedings of the* 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, 681–691. San Diego, California: Association for Computational Linguistics.

Li, J.; Monroe, W.; and Jurafsky, D. 2017. Understanding Neural Networks through Representation Erasure. arXiv:1612.08220.

Liu, Y.; Ott, M.; Goyal, N.; Du, J.; Joshi, M.; Chen, D.; Levy, O.; Lewis, M.; Zettlemoyer, L.; and Stoyanov, V. 2019. RoBERTa: A Robustly Optimized BERT Pretraining Approach. arXiv:1907.11692.

Lundberg, S.; and Lee, S.-I. 2017. A Unified Approach to Interpreting Model Predictions. arXiv:1705.07874.

Mehri, F.; Fayyaz, M.; Baghshah, M. S.; and Pilehvar, M. T. 2024. SkipPLUS: Skip the First Few Layers to Better Explain Vision Transformers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops*, 204–215.

Modarressi, A.; Fayyaz, M.; Aghazadeh, E.; Yaghoobzadeh, Y.; and Pilehvar, M. T. 2023. DecompX: Explaining Transformers Decisions by Propagating Token Decomposition. In Rogers, A.; Boyd-Graber, J.; and Okazaki, N., eds., *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, 2649–2664. Toronto, Canada: Association for Computational Linguistics.

Modarressi, A.; Fayyaz, M.; Yaghoobzadeh, Y.; and Pilehvar, M. T. 2022. GlobEnc: Quantifying Global Token Attribution by Incorporating the Whole Encoder Layer in Transformers. In Carpuat, M.; de Marneffe, M.-C.; and Meza Ruiz, I. V., eds., *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 258–271. Seattle, United States: Association for Computational Linguistics.

Mohebbi, H.; Zuidema, W.; Chrupała, G.; and Alishahi, A. 2023. Quantifying Context Mixing in Transformers. In Vlachos, A.; and Augenstein, I., eds., *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, 3378–3400. Dubrovnik, Croatia: Association for Computational Linguistics.

Oyama, M.; Yokoi, S.; and Shimodaira, H. 2023. Norm of Word Embedding Encodes Information Gain. In Bouamor, H.; Pino, J.; and Bali, K., eds., *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, 2108–2130. Singapore: Association for Computational Linguistics.

Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. "Why Should I Trust You?": Explaining the Predictions of Any Classifier. arXiv:1602.04938.

Samek, W.; Binder, A.; Montavon, G.; Bach, S.; and Müller, K. 2015. Evaluating the visualization of what a Deep Neural Network has learned. *CoRR*, abs/1509.06321.

Serrano, S.; and Smith, N. A. 2019. Is Attention Interpretable? In Korhonen, A.; Traum, D.; and Màrquez, L., eds., *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2931–2951. Florence, Italy: Association for Computational Linguistics.

Simonyan, K.; Vedaldi, A.; and Zisserman, A. 2014. Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps. arXiv:1312.6034.

Smilkov, D.; Thorat, N.; Kim, B.; Viégas, F.; and Wattenberg, M. 2017. SmoothGrad: removing noise by adding noise. arXiv:1706.03825.

Socher, R.; Perelygin, A.; Wu, J.; Chuang, J.; Manning, C. D.; Ng, A.; and Potts, C. 2013. Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank. In Yarowsky, D.; Baldwin, T.; Korhonen, A.; Livescu, K.; and Bethard, S., eds., *Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing*, 1631–1642. Seattle, Washington, USA: Association for Computational Linguistics.

Sundararajan, M.; Taly, A.; and Yan, Q. 2017. Axiomatic Attribution for Deep Networks. In Precup, D.; and Teh, Y. W., eds., *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, 3319–3328. PMLR.

Touvron, H.; Martin, L.; Stone, K. R.; Albert, P.; Almahairi, A.; Babaei, Y.; Bashlykov, N.; Batra, S.; Bhargava, P.; Bhosale, S.; Bikel, D. M.; Blecher, L.; Ferrer, C. C.; Chen, M.; Cucurull, G.; Esiobu, D.; Fernandes, J.; Fu, J.; Fu, W.; Fuller, B.; Gao, C.; Goswami, V.; Goyal, N.; Hartshorn, A. S.; Hosseini, S.; Hou, R.; Inan, H.; Kardas, M.; Kerkez, V.; Khabsa, M.; Kloumann, I. M.; Korenev, A. V.; Koura, P. S.; Lachaux, M.-A.; Lavril, T.; Lee, J.; Liskovich, D.; Lu, Y.; Mao, Y.; Martinet, X.; Mihaylov, T.; Mishra, P.; Molybog, I.; Nie, Y.; Poulton, A.; Reizenstein, J.; Rungta, R.; Saladi, K.; Schelten, A.; Silva, R.; Smith, E. M.; Subramanian, R.; Tan, X.; Tang, B.; Taylor, R.; Williams, A.; Kuan, J. X.; Xu, P.; Yan, Z.; Zarov, I.; Zhang, Y.; Fan, A.; Kambadur, M.; Narang, S.; Rodriguez, A.; Stojnic, R.; Edunov, S.; and Scialom, T. 2023. Llama 2: Open Foundation and Fine-Tuned Chat Models. ArXiv, abs/2307.09288.

Wang, J.; Tuyls, J.; Wallace, E.; and Singh, S. 2020. Gradient-based Analysis of NLP Models is Manipulable. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, 247–258. Online: Association for Computational Linguistics.

Warstadt, A.; Parrish, A.; Liu, H.; Mohananey, A.; Peng, W.; Wang, S.-F.; and Bowman, S. R. 2020. BLiMP: A Benchmark of Linguistic Minimal Pairs for English. In Ettinger, A.; Jarosz, G.; and Pater, J., eds., *Proceedings of the Society for Computation in Linguistics 2020*, 409–410. New York, New York: Association for Computational Linguistics.

Williams, A.; Nangia, N.; and Bowman, S. 2018. A Broad-Coverage Challenge Corpus for Sentence Understanding through Inference. In Walker, M.; Ji, H.; and Stent, A., eds., Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), 1112–1122. New Orleans, Louisiana: Association for Computational Linguistics.

Wolf, T.; Debut, L.; Sanh, V.; Chaumond, J.; Delangue, C.; Moi, A.; Cistac, P.; Rault, T.; Louf, R.; Funtowicz, M.; Davison, J.; Shleifer, S.; von Platen, P.; Ma, C.; Jernite, Y.; Plu, J.; Xu, C.; Le Scao, T.; Gugger, S.; Drame, M.; Lhoest, Q.; and Rush, A. 2020. Transformers: State-of-the-Art Natural Language Processing. In Liu, Q.; and Schlangen, D., eds., *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, 38–45. Online: Association for Computational Linguistics.

Yin, K.; and Neubig, G. 2022. Interpreting Language Models with Contrastive Explanations. arXiv:2202.10419.

A Appendix

A.1 Computing Infrastructure

All experiments were conducted on a machine with an Nvidia Quadro RTX 8000 GPU with 48GB of memory. The operating system used is Ubuntu 22.04.3 LTS. The 'requirements.txt' file included in the code appendix lists all the necessary software libraries and frameworks, along with their respective versions.

A.2 Experiment 1: Complete Results

Figures 6 to 12 illustrate the AOPC and Accuracy across different models and datasets. In Figure 7, we demonstrate the global performance of Value Zeroing on the SST-2 dataset. The results show that this method is not faithful to the model's decision-making process. This issue may stem from the inherent limitations of the rollout aggregation method, as previously discussed. Additionally, since Value Zeroing is a perturbation-based method, it may also inherit some of the challenges associated with these approaches. For instance, this method zeros out each token's value vector one at a time, which can lead to problems like ignoring dependencies between features. Consider the following example:

"The movie is mediocre, maybe even bad."

In this case, erasing *"mediocre"* or *"bad"* independently may not significantly impact the overall sentiment of the sentence.

For our Integrated Gradients experiments, we generally used 50 steps. However, for LLAMA2, we reduced the number of steps to 25 due to resource constraints.



Figure 7: AOPC of different attribution methods for BERT fine-tuned on SST-2 (higher AOPC is better).



Figure 8: AOPC of different attribution methods for LLAMA2 fine-tuned on MultiNLI (higher AOPC is better).



Figure 9: AOPC of different attribution methods for De-BERTa fine-tuned on MultiNLI (higher AOPC is better).



Figure 6: AOPC of different attribution methods for De-BERTa fine-tuned on SST-2 (higher AOPC is better).



Figure 10: AOPC of different attribution methods for BERT fine-tuned on MultiNLI (higher AOPC is better).



Figure 11: Accuracy of different attribution methods for LLAMA2 fine-tuned on STS-B (lower Accuracy is better).



Figure 12: Accuracy of different attribution methods for De-BERTa fine-tuned on STS-B (lower Accuracy is better).

A.3 Experiment 2: RoBERTa Complete Results

The evidence alignment experiment is conducted on a masked language modeling task to understand why a particular target token is chosen. The LogAt method provides perlabel attribution scores, enabling us to apply it to other labels (i.e., tokens in the vocabulary) to identify the most important tokens in the input sequence for predicting each specific label. Figures 13 and 14 display the results of the Dot Product and Average Precision alignment metrics for the pretrained RoBERTa model. An important observation is the notable performance of LogAt("plural"), which demonstrates its effectiveness in identifying evidence words. This level of performance is not seen with two other randomly chosen words. Specifically, the results are more pronounced in the top layers, indicating that increased context mixing enhances the connection between the evidence and the word "plural." In other words, as we progress through the layers, the contextualized representation of the evidence word becomes increasingly similar to the word "plural," resulting in a higher attribution for this word. We attribute the superior performance for the word "plural" primarily to the nature of the phenomena used from the BLIMP dataset, which focused on number agreement. Figures 15 and 16 demonstrate the results for the fine-tuned RoBERTa model.



Figure 13: Per-layer alignment between evidence and explanation vectors for the pre-trained version of RoBERTa, calculated using Dot Product metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.14.

12	0.11	0.09	0.13	0.08	0.11	0.11	0.15	0.14	0.15	0.14	0.22		
11	0.11		0.16		0.09		0.15	0.16	0.07	0.15	0.15		- 0.25
10	0.11	0.09		0.09	0.08	0.10	0.15	0.15	0.09	0.16	0.18		
6	0.11		0.16		0.08		0.16	0.16	0.11	0.15	0.22		- 0.20
00	0.11	0.10			0.08		0.16	0.16	0.12	0.15	0.24		
er 7	0.11	0.11			0.06	0.11	0.16	0.15	0.13	0.10	0.28		- 0.15
6 6	0.11				0.06		0.16	0.19	0.09	0.08	0.24		
ŝ	0.11				0.05			0.15	0.10		0.23		- 0 1 0
4	0.11	0.10		0.09	0.08			0.16	0.14		0.22		0.10
m	0.11				0.06				0.11		0.21		
2	0.11	0.11	0.15	0.15	0.01				0.12	0.08			- 0.05
ч	0.11	0.11	0.10		0.04			0.17	0.15	0.09			
	Random Baseline	GlobEnc~	ALTI-	Value Zeroing	12 norm	LogAt(Foil)	LogAt(Target)	NormXLogit	LogAt("noun")	LogAt("apple")	LogAt("plural")		

Figure 15: Per-layer alignment between evidence and explanation vectors for the fine-tuned version of RoBERTa, calculated using Dot Product metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.14.

12	0.28	0.35	0.39	0.36	0.33	0.33	0.35	0.33	0.40	0.31	0.45	
11			0.37		0.17	0.36	0.38	0.38	0.41	0.36	0.47	- 0.45
10					0.22			0.33	0.36	0.38	0.47	
6			0.35	0.34	0.22		0.35	0.36	0.38	0.35	0.47	- 0.40
00		0.35	0.36	0.37	0.21			0.33	0.38	0.36	0.46	
er 7		0.28	0.35		0.17		0.37	0.36	0.38	0.38	0.49	- 0.35
6 6	0.28	0.34	0.37	0.36	0.18	0.36	0.39	0.39	0.28		0.44	- 0.20
ŝ			0.37		0.17	0.35	0.35	0.36	0.28		0.42	- 0.50
4	0.28	0.27		0.26	0.17	0.35	0.35	0.35	0.35		0.42	- 0.25
m		0.37	0.39	0.37	0.17			0.34	0.31		0.41	
2		0.34	0.38	0.36	0.16			0.32	0.32	0.26	0.36	- 0.20
г			0.25		0.17	0.35	0.35	0.35	0.33	0.25	0.35	
	Random Baseline	GlobEn _{C ¬}	ALTIN	Value Zeroing	12 norm	^{Lo} gAt(Foil)	LogAt(Target)	^{NormXLogit}	LogAt("noun")	LogAt("apple")	LogAt("plural")	

Figure 14: Per-layer alignment between evidence and explanation vectors for the pre-trained version of RoBERTa, calculated using Average Precision metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.35.

												0.50
12	0.28	0.23		0.22			0.35		0.33		0.43	- 0.50
11		0.36	0.40	0.36	0.17		0.36	0.36	0.23	0.37		- 0.45
10		0.27		0.29	0.20	0.28	0.35		0.26	0.37	0.40	
6	0.29	0.37	0.40	0.38	0.21		0.36	0.36	0.32	0.36	0.46	- 0.40
00		0.29			0.21		0.36	0.36	0.35		0.47	
er 7		0.28	0.35		0.19		0.36	0.35	0.33		0.50	- 0.35
6 6	0.28				0.19		0.38	0.38	0.26	0.26	0.46	
5					0.17			0.35	0.29		0.44	- 0.30
4	0.28	0.27		0.26	0.17	0.35	0.36	0.36	0.34		0.44	0.25
m		0.37	0.38	0.37	0.17		0.35	0.35	0.30		0.42	- 0.25
2	0.29		0.38	0.35	0.17				0.32	0.25	0.37	- 0.20
ч			0.25		0.17	0.35	0.35	0.36	0.33	0.26	0.35	
	dom B _{àseline}	GlobEnc.,	ALTI-	^{Value} Zeroing	P norm	LogAt(Foil)	LogAt(Target)	^{NormXLogit}	LogAt("noun")	ogAt("apple")	ogAt("plural")	
	lar										7	

Figure 16: Per-layer alignment between evidence and explanation vectors for the fine-tuned version of RoBERTa, calculated using Average Precision metric (higher values are better). The alignment for ℓ^2 norm of word embeddings (layer 0) is 0.35.

Reproducibility Checklist B

This paper:

• Includes a conceptual outline and/or pseudocode description of AI methods introduced (ves/partial/no/NA)

Yes. Section 3. Proposed Approach. A detailed conceptual explanation is provided. Also, you can refer to Figure 1(b) which can be helpful to better understand the approach.

· Clearly delineates statements that are opinions, hypothesis, and speculation from objective facts and results (yes/no)

Yes.

· Provides well marked pedagogical references for lessfamiliar readers to gain background necessary to replicate the paper (yes/no)

Yes. We have provided references to fundamental papers and methods where necessary, especially in sections 1. Introduction and 2. Related Work.

Does this paper make theoretical contributions? (yes/no) No.

Does this paper rely on one or more datasets? (yes/no) Yes.

- · A motivation is given for why the experiments are conducted on the selected datasets (yes/partial/no/NA) Yes. The motivation for the choice of datasets is provided in the "Data" paragraphs within Sections 4.1 and 5.1 under "Experimental Setup".
- All novel datasets introduced in this paper are included in a data appendix. (yes/partial/no/NA)

NA. No novel datasets are introduced in this paper.

• All novel datasets introduced in this paper will be made publicly available upon publication of the paper with a license that allows free usage for research purposes. (yes/partial/no/NA)

NA.

- All datasets drawn from the existing literature (potentially including authors' own previously published work) are accompanied by appropriate citations. (yes/no/NA) Yes.
- All datasets drawn from the existing literature (potentially including authors' own previously published work) are publicly available. (yes/partial/no/NA) Yes.
- All datasets that are not publicly available are described in detail, with explanation why publicly available alternatives are not scientifically satisficing. (yes/partial/no/NA) NA.

Does this paper include computational experiments? (yes/no) Yes.

• Any code required for pre-processing data is included in the appendix. (yes/partial/no).

Yes. The code is provided as supplementary material (code appendix).

• All source code required for conducting and analyzing the experiments is included in a code appendix. (yes/partial/no)

Yes.

- All source code required for conducting and analyzing the experiments will be made publicly available upon publication of the paper with a license that allows free usage for research purposes. (yes/partial/no) Yes.
- All source code implementing new methods have comments detailing the implementation, with references to the paper where each step comes from (yes/partial/no)

Partial. All source code includes detailed comments explaining the implementation. However, specific references to the paper for each step are not particularly provided. Instead, different files are organized for each setup to reduce ambiguity and facilitate understanding.

• If an algorithm depends on randomness, then the method used for setting seeds is described in a way sufficient to allow replication of results. (yes/partial/no/NA)

Yes. We have set seeds for all experiments to ensure reproducibility. The seed values are available in the code appendix separately for each file.

This paper specifies the computing infrastructure used for running experiments (hardware and software), including GPU/CPU models; amount of memory; operating system; names and versions of relevant software libraries and frameworks. (yes/partial/no)

Yes.

• This paper formally describes evaluation metrics used and explains the motivation for choosing these metrics. (yes/partial/no)

Partial. This paper formally describes all evaluation and alignment metrics used in both experiments. While the motivation for choosing each metric is not explicitly stated, these metrics are widely recognized in the literature and were selected to facilitate a meaningful comparison between our method and existing approaches.

- This paper states the number of algorithm runs used to compute each reported result. (yes/no) No.
- Analysis of experiments goes beyond single-dimensional summaries of performance (e.g., average; median) to include measures of variation, confidence, or other distributional information. (yes/no) No.

- The significance of any improvement or decrease in performance is judged using appropriate statistical tests (e.g., Wilcoxon signed-rank). (yes/partial/no) No.
- This paper lists all final (hyper-)parameters used for each model/algorithm in the paper's experiments. (yes/partial/no/NA)

Partial. Some hyperparameter details are provided in the paper and the technical appendix, with the remaining details available in the code appendix.

• This paper states the number and range of values tried per (hyper-) parameter during development of the paper, along with the criterion used for selecting the final parameter setting. (yes/partial/no/NA)

NA. The focus of this paper is not on hyperparameter tuning but rather on investigating a fine-tuned model. Therefore, detailed experimentation with different hyperparameter values was not central to our work. However, for hyperparameters related to attribution methods, we have provided relevant details where applicable.