IMPROVING ATTENTION-BASED INTERPRETABILITY OF TEXT CLASSIFICATION TRANSFORMERS

A PREPRINT

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September 23, 2022

ABSTRACT

Transformers are widely used in NLP, where they consistently achieve state-of-the-art performance. This is due to their attention-based architecture, which allows them to model rich linguistic relations between words. However, transformers are difficult to interpret. Being able to provide reasoning for its decisions is an important property for a model in domains where human lives are affected, such as hate speech detection and biomedicine. With transformers finding wide use in these fields, the need for interpretability techniques tailored to them arises. The effectiveness of attention-based interpretability techniques for transformers in text classification is studied in this work. Despite concerns about attention-based interpretations in the literature, we show that, with proper setup, attention may be used in such tasks with results comparable to state-of-the-art techniques, while also being faster and friendlier to the environment. We validate our claims with a series of experiments that employ a new feature importance metric.

Keywords Interpretable Machine Learning · Local Interpretations · Transformers · Attention · Text Classification

1 Introduction

Transformers \cite{1} have become the dominant approach for tackling NLP tasks, surpassing previous convolutional and recurrent neural network models \cite{2,3}. Transformers, however, are not easily interpretable. The large number of their parameters makes it difficult to explain their decisions. Interpretability is important in high-risk AI applications where decision-making systems can have a significant impact on human lives \cite{4}.

The most popular transformer-specific interpretability approach is the use of attention scores. Since attentions are computed during inference, obtaining interpretations from them adds no computational overhead. However, the use of attention to produce explanations has been met with skepticism by some researchers \cite{5}. Beyond attention, research focuses on transformer-specific interpretability approaches, such as combining attention with gradient information \cite{6} or computing new attentions based on network’s residual connections \cite{7}. Nevertheless, such techniques often require some additional elements in the model’s architecture, which can lead to additional training steps.

The main goal of this paper is to investigate whether there is any room for improvement in using attention for interpreting text classification transformers. Towards this goal, we contribute: i) a review of different operations applied on the attention matrices of heads and layers, and different interpretation extraction strategies (Figure \ref{fig:1}) in Section \ref{sec:3} ii) a method that selects the best combination of these operations and strategies for a given set of instances via unsupervised evaluation (Section \ref{sec:3.1}), iii) a new metric for unsupervised evaluation of interpretations that correlates better with supervised evaluation metrics (Section \ref{sec:4}), iv) replacement of each token with [UNK] as an alternative to removing it, leading to more robust interpretability evaluation (Section \ref{sec:4.1}).

Our contributions are empirically assessed on four data sets from two high risk domains: hate speech detection and biomedicine. Decision making in such domains can have a significant impact on human lives. The former by affecting
freedom of speech or allowing the incitement of violence, and the latter by inappropriate treatments. Results show that attention-based interpretations can achieve competitive results compared to the state-of-the-art neural specific technique of Integrated Gradients, while being less computationally expensive.

2 Related Work

This section presents work relevant to ours regarding methods for transformer interpretability and metrics used to evaluate such methods.

2.1 Transformer interpretability

Several interpretability techniques can be applied to transformers. A lot of studies compare existing techniques for transformers, providing ready-to-use libraries, whereas, others introduce innovative and transformer-specific interpretability techniques.

LIME [8] and SHAP [9], two model-agnostic, local interpretation approaches, can be easily applied to a transformer by just probing it for predictions. Backpropagation-based neural-specific techniques such as LRP [10], Integrated Gradients (IG) [11], and GradCam [12] can be modified to provide interpretations for transformer models. Such techniques that consider model architecture and employ back-propagated gradients are expected to yield more meaningful interpretations. However, some studies have shown that model-agnostic methods achieve competitive performance in transformer explainability [13].

The open-source library Ecco [14] offers a variety of tools that analyze the inner workings of a transformer, such as how the model’s hidden states change from layer to layer, by enabling the examination of activation vectors. Thermostat [15] is a collection of transformer interpretability techniques, including LIME, Integrated Gradients, and Shapley Values,
that aims to minimize the environmental impact and economic barriers associated with repetitive execution of common experiments in interpretable NLP. It produces feature attribution maps across different data sets, models, and techniques.

Extracting information from transformers’ attention modules has been a popular method of interpreting their decisions [16, 17], especially before its heavy criticism [5, 18]. Development of tools for visualizing these attentions, such as BertViz [19], gives us insight about how tokens of a particular sentence affect each other, while also shedding light on what each attention head and layer focuses on. Five distinct patterns of self-attention that are used across attention heads were discovered by displaying attention score heatmaps for BERT [20]. Additionally, it was shown, that by disabling certain attention heads or layers, the model does not necessarily display a decrease in performance and can even exhibit improvements in specific cases.

Towards a more effective visualization tool, a process aimed at quantifying how attention information flows from layer to layer is also introduced [7]. Specifically, two methods based on Directed Acyclic Graphs are proposed, Attention Rollout and Attention Flow, that compute attentions for each input token. Both methods take into account the models’ residual connections to obtain token attentions. These attentions were found to retain more information, and can serve as a better visualization tool.

An explainability method based on hierarchical transformer models was proposed in [21]. In this study, two different model architectures based on transformers were introduced to classify and extract explanations for sentiment analysis. Explanations were extracted based on attention weights and were compared to ones provided by human users. A recent method that does not solely rely on raw attention scores to provide explanations, is combining relevance and gradient information [6]. Specifically, relevance scores are produced for each attention head in each layer, leveraging the theory underpinning LRP. These results are then integrated with gradient information. The produced explanation is a matrix of size $S \times S$, where $S$ denotes sequence length. The final relevance map is derived from the row of the matrix corresponding to $|CLS|$ token.

### 2.2 Interpretability metrics

The most appropriate way to evaluate an interpretability technique is via a user study, where end users compare interpretations [22]. However, this kind of experimental procedure is not always feasible, due to its costly and time-consuming nature. Furthermore, human evaluation is prone to bias [23].

Ground truth interpretations provided by human annotators are called rationales [24]. When available, we can use standard metrics, such as $F_1$ or the area under the precision-recall curve (AUPRC), to evaluate interpretations. Unfortunately, datasets accompanied by rationales are scarce. Moreover, as in human evaluation, since rationales are provided by humans, erroneous, noisy, and biased annotations may occur.

There are also metrics that can work without end users, by evaluating certain properties of the produced interpretations. Robustness [25] concerns the stability of a technique. By slightly modifying the examined instances, robustness measures the degree of change between the interpretations for the initial and modified instances. The smaller this change is, the higher the robustness of the technique. Comprehensibility [26] calculates the percentage of non-zero weights in an interpretation. The lower this number, the easier for end users to comprehend the interpretation.

A frequently used family of metrics are those emulating the behavior of a user that interacts with the model to explore the validity of a given interpretation. Faithfulness [27], eliminates the token with the highest importance score from the examined instance and measures how much the prediction changes. Higher changes signify better interpretations. Truthfulness [28] removes all tokens of an instance, one at a time, and awards or penalizes the technique based on the model’s behavior.

### 3 Attention-based Interpretation Extraction

Attention information exists in the matrices of each encoder/decoder and their attention heads [29]. Attention matrices are comprised of scalar values denoting attention scores between token pairs. Intuitively, each row of the matrix indicates a token’s attention towards others, while each column represents the attention each token receives from others. Extracting interpretations from these attention matrices is not straightforward. Several approaches have been followed in the literature. However, no extensive study has been conducted insofar, to discover the most appropriate way to perform this task. This work aims to fill this gap.

The most commonly used operations in the literature for combining information from attention matrices produced by heads are averaging [30, 13, 6] and summing [31, 32]. Similarly, averaging [32] and multiplying [6] are the most common operations for layers.
Regarding how the interpretation is produced, some approaches are selecting the row corresponding to the [CLS] token (F: From [CLS]) \[6, 13\], selecting the maximum value from each column (MxC: Max Columns) \[32\] or averaging the columns of the attention matrix (MC: Mean Columns) \[33\]. These approaches for extracting interpretations from the attention matrix are shown in Figure 2.

**Figure 2: Interpretation extraction strategies from an attention matrix**

Inspired by the literature, we consider an additional similar strategy that uses the attention scores each token has towards [CLS] (T: To [CLS], also visible in Figure 2). Since [CLS] is used by a transformer for its final decision regarding an instance in text classification, we expect attention scores towards it to provide a rationale for its decision.

### 3.1 Best attention setup identification via unsupervised evaluation

We hypothesize that different combinations of head operations, layer operations and interpretation strategies will lead to different interpretation quality in different datasets or even in different instances of the same dataset. We therefore propose applying multiple such different combinations and selecting the best one according to an unsupervised interpretability evaluation method, like faithfulness.

The available operators found in the literature for attention heads were averaging and summing, while multiplying and averaging are commonly used for layers. We, additionally, experiment with summing attention layers as an additional operation, as well as selecting specific attention heads or layers, as different attention heads and layers hold different information. An additional strategy for selecting the most informative heads from each layer, inspired by a recent study \[34\], was also examined. However, it proved inefficient in our experiments, and thus no further details are discussed. Finally, we consider 4 different strategies to derive interpretations from the attention matrix, namely, \(F: \text{From [CLS]}\), \(T: \text{To [CLS]}\), \(\text{MC: Mean Columns}\), and \(\text{MxC: Max Columns}\). Eventually the available number of setups is \(3 + A \times 2 + K \times 4\) (from, to, mean columns, max columns).

### 4 Ranked Faithful Truthfulness

Faithfulness and truthfulness, albeit informative, suffer from shortcomings. Faithfulness considers solely the token with the highest importance, while truthfulness assigns the same penalty for each token regardless of its importance score. We propose a new evaluation metric called RFT (Ranked Faithful Truthfulness), which not only considers each token when evaluating the quality of the explanation, but also assigns a different penalty to each one based on their importance.

Let \(f\) be a binary classification model that can take as input a sequence of tokens \(x\) and returns the probability \(f(x)\) that \(x\) belongs to the positive class. Let \(x\) be a sequence of \(N\) tokens \(t_i, i = 1 \ldots N\) and \(w\) a corresponding vector of feature importance values \(w_i, i = 1 \ldots N\) obtained as a local explanation for prediction \(f(x)\).
RFT performs $N$ independent modifications to $x$, each time removing a different token, $t_i$, leading to instance $x^{(-i)}$. For each modification, it computes a faithfulness score $v$ based on $w_i$ and the difference of $f(x)$ and $f(x^{(-i)})$ as follows:

$$v(x, w, i) = \begin{cases} f(x) - f(x^{(-i)}), & \text{if } w_i > 0, \\ f(x^{(-i)}) - f(x), & \text{if } w_i < 0, \\ -|f(x) - f(x^{(-i)})|, & \text{if } w_i = 0 \end{cases}$$

(1)

For non-zero weights, this score is positive (negative) when the change in prediction aligns (contrasts) with our expectations given the weight of the model. For zero weights, it is negative or zero. In all cases, its magnitude corresponds to the absolute value of the difference in predictions.

In addition, RFT normalizes this score proportionally to the importance of each token. An intuitive way to achieve this would be to multiply it by the absolute value of the token importance $|w_i|$. However, this would result in information loss, as the prediction changes of zero weights would not be taken into account. We instead divide the score by the rank $r(t_i)$ of token $t_i$ based on the absolute value of its weight. For example, the ranks of 3 tokens with importance values -0.1, 0.3, 0.2, would be 3, 1 and 2, respectively. Given a sequence $x$ of length $N$ and corresponding importance weights $w$, Equation $2$ provides the definition of RFT. Higher RFT values indicate better performance.

$$\text{RFT}(x, w) = \frac{1}{N} \sum_{i=1}^{N} \frac{v(x, w, i)}{r(t_i)}$$

(2)

Given a set of instances, we can compute the average value of RFT across all instances. In the case of multi-label classification tasks, we can average RFT across all labels. In both cases, we could consider either all instances, or only those where the positive class is predicted.

4.1 Token replacement by [UNK]

Faithfulness-oriented metrics, including RFT, evaluate the performance of an interpretability method based on how the model’s decision changes when one or more tokens of the input is removed. This however affects the context for the rest of the tokens, which is important in sequence processing models, like recurrent neural networks and transformers, and even more so, if they use positional encoding, which is the standard for transformer models. To address this issue, we propose to replace tokens with [UNK] instead of deleting them. This way, we nullify the influence of the replaced token, while minimally affecting the context.

Figure 3 shows an example of such a change in attentions, where image (a) presents the attentions of the initial sequence, (b) after the most important token is removed, and (c) when replaced with [UNK]. We can see that removing the token affects attentions between the remaining tokens more than replacing it with [UNK]. For example, the attention metric towards amazing is 0.07 in the original. By removing is attention increases to 0.12, which is to be expected since the context of the sequence changed, as these tokens are next to each other. On the other hand, replacing is with [UNK], increases attention slightly to 0.08, since this change does not affect the positions of the tokens.

![Figure 3: Example of attention with token removal and replacement with [UNK]](image-url)
5 Experiments

We assess the performance of LIME and IG, as well as the attention variations outlined in the preceding section, on two transformers, DistilBERT and BERT (Appendix B). These techniques are acclaimed and widely used in literature and industry, and provide a fair comparison. Evaluation was performed using RFT (Section 4), as well as metrics discussed in Section 2 modified for use in multi-label tasks. Larger scores are preferred. Comprehensibility metric considers values below a certain threshold as zero during its evaluation. In our case, this threshold is 0.01, since each interpretation is scaled to \([-1, 1]\) by dividing its weights with the maximum absolute value, among them. Lower values on this metric are generally favored in literature \([35]\) since they indicate more comprehensive interpretations. However, depending on the user or the application, higher values may be preferred. Furthermore, we include the AUPRC metric in data sets where ground truth interpretations are present, and thus use of supervised metrics is possible. Higher scores on this metric signify better performance. Code is available in our GitHub repo.\(^1\)

Each metric is calculated on the labels predicted by the model for each instance. In the single-label scenario, we measure the performance only on the positive class. Regarding multi-label adaptations, the results are averaged across the predicted labels. Since attention-based interpretations concern the whole label set, hence, each label has the same interpretation, it has a slight disadvantage in multi-label settings.

| Data set | Domain | Rationales | Instances | Mean Size | Labels |
|----------|--------|------------|-----------|-----------|--------|
| Ethos    | Hate Speech | -         | 433       | 20.41     | 8      |
| HX       | Hate Speech | token     | 13749     | 23.86     | 1      |
| AIS      | Biomedical | -         | 3024      | 44.78     | 1      |
| HoC      | Biomedical | sentence  | 1852      | 244.43    | 10     |

We experiment with Ethos \([36]\) and HateXplain (HX) \([13]\) from the hate speech domain, as well as Hallmarks of Cancer (HoC) \([37]\) and Acute Ischemic Stroke (AIS) \([38]\), from biomedicine. AIS and HX are single-label, while the other two are multi-label. HX has token-level ground truth rationales, while HoC has sentence-level. The remaining two have no rationales. This information along with the number of instances, mean length and number of labels for these data sets is presented in Table 1. Preprocessing and experimental setup details, as well as the process of converting token-level interpretations to sentence-level, can be seen in Appendix A.

5.1 Metric and token handling evaluation

The goal of this experiment is to evaluate the proposed RFT metric, as well as the proposed token replacement strategy. We use the HX data set, because the token-level ground truth information it contains allow us to compare the correlation of the unsupervised faithfulness and RFT metrics with the supervised AUPRC metric. For computational simplicity, we do not include LIME and use DistilBERT only. Table 2 presents the results.

| Technique | [UNK] removal | [UNK] removal | AUPRC |
|-----------|---------------|---------------|-------|
| IG        | 0.23          | 0.18          | 0.79  |
| Best      | 0.19          | 0.17          | 0.83  |
| Baseline  | 0.18          | 0.16          | 0.69  |
| Spearman  | 0.7 (0.19)    | 0.7 (0.19)    | 0.4 (0.51) |
| Pearson   | 0.53          | 0.64          | 0.11  |

We can see that replacing tokens with [UNK] leads to higher faithfulness and RFT scores compared to removing them. This supports our claim that token removal artificially deflates the results of these metrics. The difference is more pronounced in IG, compared to attention-based methods. This is due to, IG using gradients to produce interpretations and back propagation of gradients causes the accumulation of the token removal error. In addition, the difference is more pronounced in RFT compared to faithfulness. This happens because token handling takes place multiple times in RFT, while only once in faithfulness.

\(^1\)https://tinyurl.com/dnx9ahfc
We also see that RFT with [UNK] replacement has a very high Spearman and Pearson correlation with AUPRC and that its ranking of the three interpretability techniques is in alignment with that of AUPRC. It can therefore be considered as an appropriate unsupervised metric in lack of ground truth data. The proposed token handling strategy is crucial for RFT, as token removal leads to very low Spearman and Pearson correlation with AUPRC. This happens because it examines each token of the sequence, and the error introduced from simply removing the tokens accumulates.

Faithfulness has lower correlation with AUPRC compared to RFT and its ranking of the three techniques is not in alignment with that of AUPRC. This is expected, as faithfulness is based on the most important token only, while AUPRC is computed across all tokens. This is also the reason why [UNK] replacement does not affect its correlation with AUPRC.

5.2 Quantitative results

This section presents the results of our experimental procedure. Metrics were computed using 20% of the data set as our test set, while the remaining, 70% and 10%, were used as training and validation sets, respectively, for fine-tuning the models. We ran our experiments once for each data set, as all examined techniques besides LIME are deterministic and the computational complexity of LIME makes multiple runs prohibitive. Table 3 shows the performance of the techniques on the data sets for DistilBERT. Results regarding the same setup for BERT can be found in Appendix B (Table 6).

| Technique | RFT | Compreh. | AUPRC  | Data set |
|-----------|-----|----------|--------|----------|
| LIME      | 0.49 | 0.85     | -      | Ethos    |
| IG        | **0.55** | 0.89     | -      | HX       |
| Best      | 0.50 | 0.83     | -      |          |
| Baseline  | 0.47 | 1.0      | -      |
| LIME      | 0.16 | 0.98     | 0.64   | AIS      |
| IG        | 0.31 | 0.94     | 0.79   |          |
| Best      | **0.35** | 0.53     | **0.83** |         |
| Baseline  | 0.29 | 1.0      | 0.69   |
| LIME      | 0.06/0.08 | 0.96/0.98 | -      | HoC      |
| IG        | 0.08/0.19 | 0.87/0.96 | -      |
| Best      | **0.29/0.27** | 0.82/0.41 | -      |
| Baseline  | 0.09/0.21 | 0.87/1.0  | -      |
| LIME      | 0.08/0.12 | 0.97/0.98 | -0.41  |          |
| IG        | **0.29/0.27** | 0.50/0.96 | **-0.69** |
| Best      | 0.22/0.25 | 0.91/1.0  | -0.64  |
| Baseline  | 0.22/0.25 | 0.91/1.0  | -0.64  |

Each score in the table corresponds to the metric’s average value across all the test set instances. For AIS and HoC, a slash separates the score at the token level with that at the sentence level. Baseline refers to the most intuitive setup, namely Mean for heads, Mean for layers and From for interpretation extraction, which is a combination of the most common approaches found in the literature. Each setup was evaluated separately, with best denoting the setup that performed best based on the unsupervised metric RFT averaged across all test set instances. A better approach in terms of performance would be to calculate the best attention setup for each examined instance. However, as this Search step would have to be performed each time a new instance is available, this would increase the computational complexity of our method. Nevertheless, as the experiments in Section 5.4 suggest, even this Search procedure is less computationally expensive than the competitors in specific cases.

We can see from Table 3 that attention-based interpretations can achieve close to state-of-the-art performance. The best setup outperforms both competitors in HX and AIS (single label), while being competitive in Ethos and HoC. The baseline setup performs even better in DistilBERT, compared to BERT’s results (Appendix B).

Layer and head selection can improve the performance of attention-based interpretability, compared to the baseline. This is evident when looking at the best setup for each data set in Table 4. Concerning how the interpretation is extracted, From was present in every setup and thus is not shown there. The numbers on the table denote the specific layer and head. Last layers seem to be selected in multi-label tasks, while middle to last tend to perform better in single-label. Combinations of selection with averaging for either heads or layers tend to also perform well. In Appendix C, a visualization tool for exploring all attention setups is introduced.
Table 4: Best attention setup based on RFT metric

| Data set | Layers | Heads | Model         |
|----------|--------|-------|---------------|
| Ethos    | 10     | 10    |               |
| HX       | Mean   | 3     | BERT          |
| AIS      | 5/5    | 11/7  | (12 layers/heads) |
| HoC      | 12/12  | Mean/11 |             |
| Ethos    | 5      | Mean  |               |
| HX       | 3      | 2     | DistilBERT    |
| AIS      | Mean/5 | 3/4   | (6 layers/heads) |
| HoC      | Mean/Mean | Mean/Mean |         |

5.3 Qualitative example

Selecting a random instance from HX data set, we use DistilBERT to demonstrate the results of each technique. In Figure 4, we showcase the selected instance, having removed any tokens that may correspond to offensive or derogatory words or imply them. Red (Blue) highlighting corresponds to positive (negative) influence towards the Hate Speech prediction, with more vibrant coloring indicating a stronger influence. The first line corresponds to ground truth rationales for the examined instance. Baseline attention seems to highlight all of the sequence, while giving higher importance to tokens relevant to the decision. On the other hand, best attention correctly identifies the most important tokens, giving minimal weight to others. IG behaves similarly, assigning correct values to important tokens, while also including few irrelevant ones. Finally, LIME seems to miss some important tokens, even assigning a negative score to one.

Figure 4: Interpretation example for each examined technique on HX

5.4 Computational overhead analysis

One key advantage of using attention interpretations, is the low computational overhead since they are already computed during inference. This leads to faster response times and lower environmental impact. In contrast, techniques such as LIME and IG require additional procedures, resulting in increased computational cost.

To empirically validate this, we performed a time response analysis for each technique in HX (small sequences) and HoC (large sequences) using BERT. Additionally, we computed their carbon footprint in terms of metric tons of CO\textsubscript{2} equivalent emissions (tCO\textsubscript{2}e) based on [39]. We performed our experiments in Google Colab using a single GPU with an average power consumption of 271W. We used the formula tCO\textsubscript{2}e = KWh × kg CO\textsubscript{2}e per KWh/10\textsuperscript{3}, assuming kg CO\textsubscript{2}e/KWh to be 0.429 [39] and the formula KWh = (interpretation time × # of GPUs × avg. power/GPU × PUE)/10\textsuperscript{3}, assuming PUE (power usage effectiveness) to be 1.10. The average tCO\textsubscript{2}e per instance for each technique can be found in Table 5.

LIME stands out from the others having the highest tCO\textsubscript{2}e in both data sets. IG is one (two) order(s) of magnitude environmentally friendlier than LIME for long (short) sequences. The baseline and identified best interpretations have the least negative impact on the environment, as their tCO\textsubscript{2}e is much lower. Search denotes the procedure of identifying the best setup for a single instance. However, this procedure could be performed only once after training to determine the best setup across a test set, and then use this identified setup to explain new instances, as performed in the experiments of Section 5.2.

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https://tinyurl.com/2u8zek8
Table 5: Average time response and tCO$_{2e}$ emissions

| Method          | HateXplain Seconds | tCO$_{2e}$ | HoC Seconds | tCO$_{2e}$ |
|-----------------|---------------------|------------|-------------|------------|
| LIME            | 57.6535             | 2.05E-06   | 164.6608    | 5.85E-06   |
| IG              | 0.4684              | 1.66E-08   | 16.4497     | 5.84E-07   |
| Identified Best | 0.0004              | 1.47E-11   | 0.2762      | 9.81E-09   |
| Baseline        | 0.0006              | 2.16E-11   | 0.2708      | 9.62E-09   |
| Search          | 0.0755              | 2.68E-09   | 54.3324     | 1.93E-06   |

Figure 5: Interpolated emissions for each method (Left: HX, Right: HoC)

Figure 5 presents tCO$_{2e}$ emissions for up to 1M instances. On the left, we simulate an interpretable Hate Speech detection system on a social media platform, where a large amount of data is being produced every second. Likewise, the right plot concerns interpretability-assisted semantic indexing of biomedical publications, which tend to have bigger sequences, in conjunction to the large number of publications processed each day in databases like PubMed (986K articles for 2020).

6 Conclusion

Several studies suggest that attention cannot be used as an interpretation tool, while others incorporate attention-based methods in their experiments without specifying how interpretations are produced. This work investigates various ways attention matrices are used in literature as interpretations and proposes a combination strategy to determine the best way to extract interpretations from them. Our findings imply that, when properly configured, attention can effectively be used as an interpretation tool for text classification. In addition, we demonstrate that attention can compete with other cutting-edge techniques in a series of experiments that include a new FI-based interpretability metric. Furthermore, compared to other techniques, attention is easier to implement while also being faster and less harmful to the environment.

Despite the effectiveness of attention, there are some limitations when using them. First, since interpretations originate from attention matrices, no negative values are present in them. This can be considered a drawback by users who also prefer negative importance scores. One more disadvantage is that the produced interpretation covers the whole label set. This, however, does not seem to greatly hinder its performance compared to LIME and IG which provide label specific interpretations.

In the future, we will combine label information with attention to obtain label-specific interpretations, containing negative values. We will explore how to optimize the runtime of the best setup Search step to make it even more environmentally friendly. Finally, another goal is to conduct a large-scale experiment with more data sets.

[3]https://tinyurl.com/4nprsskn
Acknowledgements

The research work was supported by the Hellenic Foundation for Research and Innovation (H.F.R.I.) under the “First Call for H.F.R.I. Research Projects to support Faculty members and Researchers and the procurement of high-cost research equipment grant” (Project Number: 514)

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A Preprocessing and Experimental Setup

No pre-processing took place for Ethos, while for AIS the max input sequence length was limited to 250. For HX and HoC we removed tags and replaced numbers with the token number for HX, while unicodes were removed from HoC. The max sequence length of HoC was limited to 300. It is worth mentioning that since Ethos and HX have smaller input sizes, the interpretations supplied by the techniques are at the token level, whereas HoC and AIS are examined both at token and sentence level, because many of their abstracts have more than 200 tokens. For the parameter setup, for LIME we chose 200 neighbors for AIS and HoC and 2000 for HX and Ethos. The selection was performed based on the input size of each data set, discussed earlier. In case of IG, we chose an interpolation step of 50 for all data sets. Following the same notation as in Section 4, we introduce the process of converting token-level interpretations to sentence-level. We identify the different sentences of $x$ and average the influence of the tokens comprising them. In particular, for each sentence $s_k$, which is a set of tokens $t_i$, we aim to extract a single weight to denote its influence. Therefore, for each $s_k = \{t_i | t_i \in k^{th} \text{ sentence}\}$, we compute the average weight of its tokens as $w^*_k = (1/|s_k|) \sum_{t_i \in s_k} w^*_i$. 

Figure 6: Screenshot of the developed attention analysis visualization tool
B  Experiments with BERT

Performing the same experiment as in Section 5.2, Table 6 shows that with the correct setup, attention achieves competitive results in all data sets, when used on BERT. Attention is outperforming the competitors in the AIS data set both in token and sentence level, while ranking second behind IG on HX and HoC. Furthermore, while the baseline setup can offer meaningful explanations, determining the best setup yields greater results.

| Technique | RFT | Compreh. | AUPRC | Data set |
|-----------|-----|----------|-------|----------|
| LIME      | 0.48| 0.80     | -     | Ethos    |
| IG        | **0.52**| 0.84 | -     | Ethos    |
| Best      | 0.44| 0.32     | -     | Ethos    |
| Baseline  | 0.42| 1.0      | -     | Ethos    |
| LIME      | 0.18| 0.97     | 0.58  | HX       |
| IG        | **0.49**| 0.90 | **0.81**| HX       |
| Best      | 0.47| 1.0      | 0.79  | HX       |
| Baseline  | 0.46| 1.0      | 0.77  | HX       |
| LIME      | 0.07/0.12| 0.89/0.98 | -    | AIS      |
| IG        | **0.08/0.16**| 0.67/0.89 | **0.81**| AIS      |
| Best      | **0.08/0.19**| 0.08/0.70 | -    | AIS      |
| Baseline  | 0.06/0.14| 0.97/1.0 | -    | AIS      |
| LIME      | 0.10/0.12| 0.96/0.98 | -0.37| HoC      |
| IG        | **0.28/0.27**| 0.46/0.94 | **0.68**| HoC      |
| Best      | **0.24/0.27**| 0.90/0.72 | **0.59**| HoC      |
| Baseline  | 0.24/0.24| 0.90/1.0 | **0.58**| HoC      |

C  Attention Analysis Visualization Tool

We also provide a visualization tool for exploring the performance of all possible attention setups across all data sets and models. The visualization tool is dockerized and can be found in our GitHub repo [https://tinyurl.com/dnx9ahfc].