Benchmarking Post-Hoc Interpretability Approaches for Transformer-based Misogyny Detection

Giuseppe Attanasio[1,2], **Debora Nozza**[1], **Eliana Pastor**[2], **Dirk Hovy**[1]

[1]Bocconi University, Milan, Italy
[2]Politecnico di Torino, Turin, Italy
{giuseppe.attanasio3,debora.nozza,dirk.hovy}@unibocconi.it,
eliana.pastor@polito.it

Abstract

Warning: This paper contains examples of language that some people may find offensive.

Transformer-based Natural Language Processing models have become the standard for hate speech detection. However, the unconscious use of these techniques for such a critical task comes with negative consequences. Various works have demonstrated that hate speech classifiers are biased. These findings have prompted efforts to explain classifiers, mainly using attribution methods. In this paper, we provide the first benchmark study of interpretability approaches for hate speech detection. We cover four post-hoc token attribution approaches to explain the predictions of Transformer-based misogyny classifiers in English and Italian. Further, we compare generated attributions to attention analysis. We find that only two algorithms provide faithful explanations aligned with human expectations. Gradient-based methods and attention, however, show inconsistent outputs, making their value for explanations questionable for hate speech detection tasks.

1 Introduction

The advent of social media has proliferated hateful content online – with severe consequences for attacked users even in real life. *Women* are often attacked online. A study by Data & Society[1] of women between 15 to 29 years showed that 41% self-censored to avoid online harassment. Of those, 21% stopped using social media, 13% stopped going online, and 4% stopped using their mobile phone altogether. These numbers demonstrate the need for automatic misogyny detection systems for moderation purposes.

	You	**are**	**a**	**smart**	**woman**
ΔP (10^{-2})	-0.1	1.1	-0.0	0.8	-47.6
G	0.11	0.10	0.09	0.25	0.27
IG	-0.17	0.18	-0.09	-0.35	-0.20
SHAP	0.00	-0.14	-0.04	-0.03	0.78
SOC	0.07	-0.13	0.03	0.03	0.52

Table 1: Explanations generated by benchmarked methods. A fine-tuned BERT wrongly classifies the text as misogynous. Darker colors indicate higher importance.

Various Natural Language Processing (NLP) models have been proposed to detect and mitigate misogynous content (Basile et al., 2019; Indurthi et al., 2019; Lees et al., 2020; Fersini et al., 2020a; Safi Samghabadi et al., 2020; Attanasio and Pastor, 2020; Guest et al., 2021; Attanasio et al., 2022). However, several papers already demonstrated that hate speech detection models suffer from unintended bias, resulting in harmful predictions for protected categories (e.g., *women*). Table 1 (top row) reports a very simple sentence that a state-of-the-art NLP model misclassifies as misogynous content.

This issue shows the need to understand the rationale behind a given prediction. A mature literature on model interpretability with applications to NLP-specific approaches exists (Ross et al., 2021; Sanyal and Ren, 2021; Rajani et al., 2019, inter-alia).[2] As explanations become part of legal regulations (Goodman and Flaxman, 2017), a growing body of work has focused on the *evaluation* of explanation approaches (Nguyen, 2018; Hase and Bansal, 2020; Nguyen and Martínez, 2020; Jacovi and Goldberg, 2020, inter-alia). However, little guidance on which interpretability method suits

[1] https://www.datasociety.net/pubs/oh/Online_Harassment_2016.pdf

[2] We refer the reader to Danilevsky et al. (2020) and Madsen et al. (2021) for a recent, thorough perspective on explanation methods for NLP models.

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best to the sensible context of misogyny identification has been given. For instance, some explanations in Table 1 hint to which token is wrongly driving the classification and even highlight a potential bias of the model. But not all of them.

We bridge this gap. We benchmark interpretability approaches to explain state-of-the-art Transformer classifiers on the task of automatic misogyny identification. We cover two benchmark Twitter datasets for misogyny detection in English and Italian (Fersini et al., 2018, 2020b). We focus on single-instance, post-hoc input attribution methods to measure the importance of each token for predicting the instance label. Our benchmark suite comprises gradient-based methods (Gradients (Simonyan et al., 2014) and Integrated Gradients (Sundararajan et al., 2017)), Shapley values-based methods (SHAP (Lundberg and Lee, 2017)), and input occlusion (Sampling-And-Occlusion (Jin et al., 2020)). We evaluate explanations in terms of plausibility and faithfulness (Jacovi and Goldberg, 2020). Table 1 reports an example of token-wise contribution computed with these methods. Furthermore, we study attention-based visualizations and compare them to token attribution methods searching for any correlation. To our knowledge, this is the first benchmarking study of feature attribution methods used to explain Transformer-based misogyny classifiers.

Our results show that SHAP and Sampling-And-Occlusion provide plausible and faithful explanations and are consequently recommended for explaining misogyny classifiers' outputs. We also find that, despite their popularity, gradient- and attention-based methods do *not* provide faithful explanations. Outputs of gradient-based explanation methods are inconsistent, while *attention does not provide any useful insights for the classification task*.

Contributions We benchmark four post-hoc explanation methods on two misogyny identification datasets across two languages, English and Italian. We evaluate explanations in terms of plausibility and faithfulness. We demonstrate that not every token attribution method provides reliable insights and that attention cannot serve as explanation. Code is available at `https://github.com/MilaNLProc/benchmarking-xai-misogyny`.

2 Benchmarking suite

In the following, we describe the scope (§2.1) of our benchmarking study, the included methods (§2.2), and the evaluation criteria (§2.2).

2.1 Scope

We consider *local* explanation methods (Lipton, 2018; Guidotti et al., 2019). Given a classification model, a data point, and a target class, these methods explain the probability assigned to the class by the model. *Global* explanations provide model- or class-wise explanations and are hence out of the scope of this work.

Among local explanation methods, we focus on *post-hoc* interpretability, i.e., we explain classification models that have already been trained. We leave out *inherently interpretable* models (Rudin, 2019) as they do not find widespread use in NLP-driven practical applications.

We restrict our study to input attribution methods. In Transformer-based language models, inputs typically correspond to the tokens' input embeddings (Madsen et al., 2021). We, therefore, refer to *token attribution* methods to generate a contribution score for each input token (or word, resulting by some aggregation of sub-word token contributions).

2.2 Methods

We benchmark three families of input token attribution methods. First, we derive token contribution using gradient attribution. These methods compute the gradient of the output with respect to each of the inputs. We compute simple gradient (G) (Simonyan et al., 2014) and integrated gradients (IG) (Sundararajan et al., 2017). Then, we attribute inputs using approximated Shapley values (SHAP) (Lundberg and Lee, 2017). Finally, following the literature on input perturbation via occlusion, we impute input contributions using Sampling-And-Occlusion (SOC) (Jin et al., 2020). See appendix A.2 for all implementation details.

Attention There is an open debate of whether attention is explanation or not (Jain and Wallace, 2019; Wiegreffe and Pinter, 2019; Bastings and Filippova, 2020). Our benchmarking study provides a perfect test-bed to understand if attention aligns with attribution methods. We compare standard self-attention with effective attention (Brunner et al., 2020; Sun and Marasović, 2021). Further, we measure attribution between input tokens and

Dataset	# Train	# Test	Hate %	F1
AMI-EN	4,000	1,000	45%	68.78
AMI-IT	5,000	1,000	47%	79.79

Table 2: Summary of datasets in terms of the number of training, validation and test tweets, percentage of hateful records within the training split, and F1-score of BERT models on test sets.

hidden representations using Hidden Token Attribution (HTA) (Brunner et al., 2020).

2.3 Evaluation criteria

We use *plausibility* and *faithfulness* as evaluation criteria (Jacovi and Goldberg, 2020). A "plausible" explanation should align with human beliefs. In our context, the provided explanation artifacts should *convince* humans that highlighted words are responsible for either misogynous speech or not.[3] A "faithful" explanation is a proxy for the true "reasoning" of the model. Gradient attributions are commonly considered faithful explanations as gradients provide a direct, mathematical measure of how variations in the input influences output. For the remaining attribution approaches, we measure faithfulness under the *linearity assumption* (Jacovi and Goldberg, 2020), i.e., the impact of certain parts of the input is independent of the rest. In our case, independent units correspond to input tokens. Following related work (Jacovi et al., 2018; Feng et al., 2018; Serrano and Smith, 2019, inter-alia), we evaluate faithfulness by erasing input tokens and measuring the variation on the model prediction. Ideally, faithful interpretations highlight tokens that change the prediction the most.

2.4 Data

Automatic misogyny identification is the binary classification task to predict whether a text is misogynous or not.[4] We focus on two recently-released datasets for misogynous content identification in English and Italian, released as part of the Automatic Misogyny Identification (AMI) shared tasks (Fersini et al., 2018, 2020b). Both datasets have been collected via keyword-based search on Twitter. Table 2 reports the dataset statistics.

3 Experimental setup

Among the Transformer-based models, we focus on BERT (Devlin et al., 2019) due to its widespread usage. We fine-tuned pre-trained BERT-based models on the AMI-EN and AMI-IT datasets. We report full details on the training in appendix A.1. Table 2 reports the macro-F1 performance of BERT models on the test splits.

We explain BERT outputs on both tweets from test sets[5] and manually-generated data. On real data, we address two questions: 1) *Is it right for the right reason?*, i.e., we assess if the model relies on a plausible set of tokens; 2) *What is the source of error?*, i.e., we aim to identify tokens that wrongly drive the classification outcome. By explaining manually-defined texts, we can probe for model biases.

Tables 3-6 report token contributions computed with benchmarked approaches (§2.2). We report contributions for individual tokens.[6] We define table contents as follows. Separately by explanation method, we first generate raw contributions and then L1-normalize the vector. Finally, we use a linear color scale between solid blue (assigned for contribution -1), white (contribution 0), and solid red (contribution 1). For all reported examples, we explain the `misogynous` class. Hence, positive contributions indicate tokens *pushing* towards the misogynous class, while negative contributions push towards the non-misogynous one. Lastly, the second top row reports the variation on the probability assigned by the model when the corresponding token is erased (ΔP).

4 Discussion

Error analysis Table 3 shows the explanations for a tweet incorrectly predicted as misogynous. IG, SHAP, and SOC assign a negative contribution to the word *boy*. This matches our expectations since the target of the hateful comment is the male gender. These explanations are thus plausible. Still, the tweet is classified as misogynous. The tokens *pu* and *##ssy* mainly drive the prediction to the misogynous class, as revealed by all explainers (SHAP and SOC in a clearer way). Ex-

[3] In this study, the human expectation corresponds to the authors'.

[4] Characterizing misogyny is a much harder task, possibly modeling complex factors such as shaming, objectification, or more. Here, we simplify the task to focus on benchmarking interpretability.

[5] We rephrase and explain rephrased versions of tweets to protect privacy.

[6] While several work average sub-word contributions for out-of-vocabulary words, there is no general agreement on whether this brings meaningful results. Indeed, an average would assume a model that leverages tokens as a single unit, while there is no clear evidence of that.

	You	pu	##ssy	boy
ΔP (10^{-2})	-0.3	-0.2	-35.6	0.8
G	0.11	0.19	0.32	0.18
IG	0.26	0.00	0.14	-0.60
SHAP	-0.03	0.52	0.28	-0.17
SOC	-0.01	0.03	0.51	-0.14

Table 3: Example from AMI-EN test set, anonymyzed text on first row. Ground truth: `non misogynous`. Prediction: `misogynous` ($P = 0.78$).

planations suggest the model is failing to assign the proper importance to the targeted gender of the hateful comment. These plausible explanations are also faithful. Removing the term *boy* increases the probability of the misogynous class while omitting tokens *pu* and *##ssy* decrease it.

We further analyze the term *p*ssy* and its role as a source of errors. Almost all tweets of the test set containing the term *p*ssy* are labeled by the model as misogynous. The false-positive rate on this set of tweets is 0.93 compared to the 0.49 of the overall test set. Similar considerations apply to English words typically associated with misogynous content as *b*tch* and *wh*re*.

Is it right for the right reason? Table 4 shows the explanation of a correctly predicted misogynous tweet. Gradient, SHAP, and SOC explanations assign a high positive contribution to slurs (*b*tch*, *s*ck*, and *d*ck*). These explanations align with human expectations. However, not all slurs impact the classification outcome. Explanations on *b*tch* are faithful but they are not for *s*ck* and *d*ck*. Differently, IG does not highlight any token with a positive contribution. This goes against expectations as the predicted class is misogynous and therefore we cannot draw conclusions.

Unintended bias We study explanations to search for errors caused by unintended bias, a known phenomenon affecting models for misogynous identification. A model suffering from unintended bias performs better (or worse) when texts mention specific identity terms (e.g., *woman*) (Dixon et al., 2018).

Table 1 reports the non-misogynous text "You are a smart woman" incorrectly labeled as misogynous. SHAP, SOC, and, to a lesser extent, Gradient explanations indicate the term *woman* as responsible for the prediction. This result matches with recent findings on the unintended bias of hateful detection models (Nozza et al., 2019; Dixon et al., 2018; Borkan et al., 2019) and therefore explanations are plausible. Removing the term *woman* causes a drop of 0.48 to the probability of the misogynous class. This validates the insight provided by the explanations. Similar to the previous examples, the explanation of IG is difficult to interpret.

Table 5 shows another example of unintended bias. The text “Ann is in the kitchen” is incorrectly labeled as misogynous. Gradients, SHAP, and SOC assign the highest positive contribution to the (commonly) female name *Ann*. Interestingly, the second most important word for Gradients and SHAP is *kitchen*, reflecting stereotypes learned by the classification model (Fersini et al., 2018). These explanations are faithful: the model prediction drops by a significant 0.40 and 0.24 when erasing the tokens *Ann* and *kitchen*, respectively. We substitute the name *Ann* with *David*, a common male name. We observe that the prediction and the explanations drastically change. The text is correctly assigned to the non-misogynous class and IG, SHAP, and SOC assign a high negative contribution to the word *David*. The all-positive contributions of Gradients do not provide useful insights.

Bias due to language-specific expressions Table 6 (left) shows an example of incorrectly predicted misogynous text in Italian: "p*rca p*ttana che gran pezzo di f*ga" ("holy sh*t what a nice piece of *ss"). The expression "*p*rca p*ttana*" (literally *pig sl*t*) is a taboo interjection commonly used in the Italian language and does not imply misogynous speech.

The interpretation of the gradient explanation is hard since all contributions are positive and associated with the misogynous class. All explanation methods assign a positive contribution to the word *f*ga* (**ss*). SHAP, SOC, and, to a lesser extent IG, indicate that the main reason behind the non-misogynous prediction is the term *p*rca*. The bias of the model towards this expression was firstly exposed in (Nozza, 2021) and it thus validates IG, SHAP, and SOC explanations as plausible. When one of the two terms of the expression is removed, the probability increases significantly. This suggests that explanations by IG, SHAP, and SOC are faithful. Further, we inspect the behavior of explanation methods when we erase one of the terms. We omit the word *p*rca* and we report its explanations on Table 6 (right). The text is correctly assigned to the misogynous class and the word

	s*ck	a	d*ck	and	choke	you	b*tch
ΔP (10^{-2})	-0.02	0.2	0.8	0.3	-0.1	0.03	-13.4
G	0.10	0.08	0.14	0.07	0.08	0.10	0.25
IG	-0.14	-0.16	-0.08	-0.05	-0.20	-0.22	-0.16
SHAP	0.24	-0.03	0.07	-0.05	0.05	-0.06	0.50
SOC	0.20	-0.02	0.26	-0.02	0.07	0.00	0.29

Table 4: Example from AMI-EN test set, anonymyzed text on first row. Ground truth: `misogynous`. Prediction: `misogynous` ($P = 0.90$).

	Ann	is	in	the	kitchen	David	is	in	the	kitchen
ΔP (10^{-2})	-40.4	15.4	12.7	-12.6	-24.3	-1.0	8.0	-1.3	-5.8	-6.7
G	0.25	0.16	0.08	0.10	0.21	0.19	0.18	0.09	0.09	0.28
IG	-0.15	0.18	0.12	-0.33	-0.22	-0.36	0.14	0.09	-0.25	-0.17
SHAP	0.27	-0.31	-0.15	-0.01	0.27	-0.29	-0.38	-0.19	-0.05	0.09
SOC	0.28	-0.19	-0.06	0.10	0.07	-0.25	-0.11	-0.03	0.04	0.05

Table 5: Manually-generated example. Text starts with a female (left) and male (right) name. Ground truth (both): `non-misogynous`. Prediction: `misogynous` ($P = 0.53$) (left), `non-misogynous` ($P = 0.14$) (right).

	p*rca	p*ttana	che	gran	pezzo	di	f*ga	p*ttana	che	gran	pezzo	di	f*ga
ΔP (10^{-2})	94.7	79.7	-0.8	-0.6	0.3	-0.7	-0.6	1.0	-2.3	-1.3	0.4	0.3	-22.9
G	0.17	0.15	0.06	0.07	0.11	0.07	0.13	0.20	0.08	0.10	0.14	0.08	0.21
IG	-0.25	-0.10	-0.09	-0.16	-0.04	0.21	0.13	-0.12	-0.03	-0.25	0.11	0.17	0.32
SHAP	-0.69	-0.01	0.01	0.05	0.05	0.05	0.14	0.15	0.10	0.13	0.10	0.10	0.43
SOC	-0.56	-0.07	0.00	0.04	0.05	-0.05	0.22	0.00	0.05	0.07	0.04	-0.12	0.57

Table 6: Manually-generated example. Complete text (left) and text without initial "p*rca" (right). Non-literal translation: "*holy sh*t what a nice piece of *ss*". Ground truth (both): `misogynous`. Prediction: `non-misogynous` ($P = 0.03$) (left), `misogynous` ($P = 0.97$) (right).

*f*ga* (**ss*) has the highest positive contribution for all the approaches.

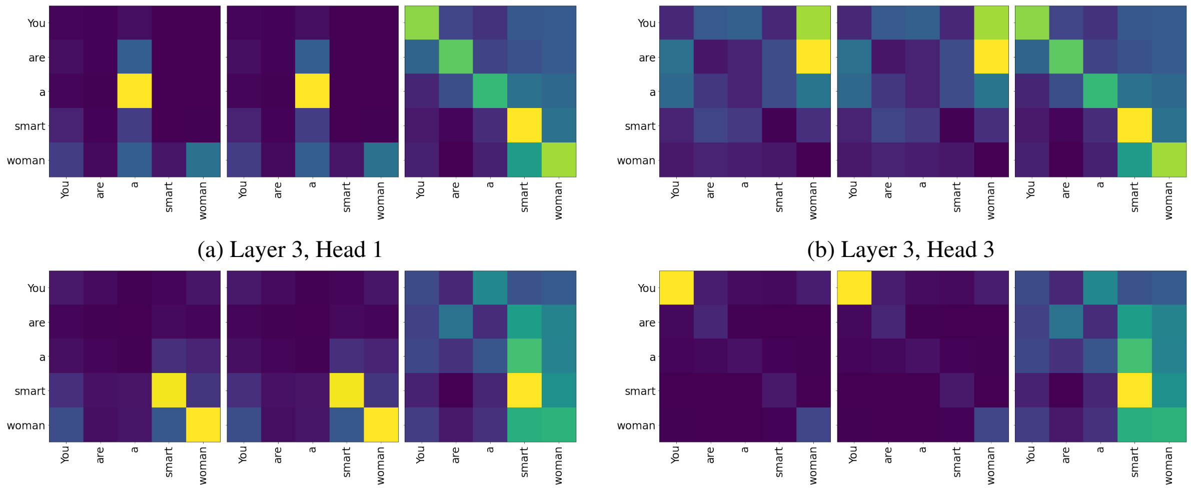
4.1 Is attention explanation?

We follow up on the open debate on attention used as an explanation, providing examples on the misogyny identification task. Figure 1 shows self-attention maps in our fine-tuned BERT at different layers and heads for the already discussed sentence "You are a smart woman". Based on our previous analysis (§4), we know that the model has an unintended bias towards the token "woman".

We cannot infer the same information from attention maps. Raw attention weights differ significantly for different layers and heads. In this example, there is a vertical pattern (Kovaleva et al., 2019) on the token "a" in layer 3 (Figure 1a). However, the pattern disappears from heads in the same layer (Figure 1b) and from the same head on deeper layers, where, instead, a block pattern characterizes "smart" and "woman" (Figure 1c). This variability hinders interpretability as no unique behavior emerges. Effective Attention (Brunner et al., 2020) is based on attention and shares the same issue.[7] These results further motivate the idea that attention gives only a *local* perspective on token contribution and contextualization (Bastings and Filippova, 2020). However, this does not provide any useful insight for the classification task. To further validate this limited scope, we use Hidden Token Attribution (Brunner et al., 2020) and measure the contribution of each input token (i.e., its first-layer token embedding) to hidden representations. On lower layers, there is a marked diagonal contribution, meaning that tokens mainly contribute to their own representation. Interestingly, on the upper layers, a strong contribution to "smart" and "woman" appears for all the tokens in the sentence. Different patterns between HTA and attention suggest that, even in the locality of a layer and a single head, attention weights do not measure token contribution.

We observed similar issues on other examples and for Italian models (see appendix B). We there-

[7] In most of our experiments, Effective Attention brings no perceptually different maps than simple Attention. The two methods are hence equivalent for local attention inspection.



(a) Layer 3, Head 1

(b) Layer 3, Head 3

(c) Layer 10, Head 1

(d) Layer 10, Head 3

Figure 1: Attention (left), Effective Attention (center), and Hidden Token Attribution (right) maps at different layers in fine-tuned BERT. Lighter colors indicate higher weights. Sentence: “You are a smart woman”.

fore cannot consider attention as a plausible nor a faithful explanation method and *discourage the use of attention to explain BERT-based misogyny classifiers*.

5 Related Work

Few works applied interpretability approaches to hate speech detection. Wang (2018) proposes an adaptation of explainability techniques for computer vision to visualize and understand the CNN-GRU classifier for hate speech (Zhang et al., 2018). Mosca et al. (2021) study both local and global explanations. They use Shapley values (Lundberg and Lee, 2017) to quantify feature importance on a *local* level and feature space exploration for a *global* explanation. Risch et al. (2020) analyze multiple attribution-based explanation methods for offensive language detection. The analysis includes an interpretable model (Naïve Bayes), model-agnostic methods based on surrogate models (LIME (Ribeiro et al., 2016), layer-wise relevance propagation (LRP) (Bach et al., 2015), and a self-explanatory model (LSTM with an attention mechanism). SHAP explainer is applied (Wich et al., 2020) to investigate the impact of political bias on hate speech classification. Sample-And-Occlusion (SOC) explanation algorithm has been used in its hierarchical version in different papers for showing the results of hate speech detection (Nozza, 2021; Kennedy et al., 2020).

In this paper, we specifically focus on hate speech against women. In this context, Godoy and Tommasel (2021) apply SHAP to derive global explanations with the aim of exploring unintended bias of Random Forest-based misogyny classifier.

While growing efforts are made for evaluating interpretability approaches for NLP models (Atanasova et al., 2020; DeYoung et al., 2020; Prasad et al., 2021; Nguyen, 2018; Hase and Bansal, 2020; Nguyen and Martínez, 2020; Jacovi and Goldberg, 2020), the evaluation is not domain-specific. Therefore, the benchmarking miss to consider specific sensitive problems and biases that are proper of the hate speech domain on which the explanation validation must focus. This paper fills this gap by focusing on post-hoc feature attribution explanation methods on individual predictions for the task of hate speech against women.

6 Conclusion

In this paper, we benchmarked different explainability approaches on Transformer-based models for the task of hate speech detection against women in English and Italian. We focus on post-hoc feature attribution methods applied to fine-tuned BERT models. Our evaluation demonstrated that SHAP and SOC provide plausible and faithful explanations and are consequently recommended for explaining misogyny classifiers’ outputs. In contrast, gradient- and attention-based approaches failed in providing reliable explanations.

As future work, we plan to add to the benchmarking suite a systematic evaluation involving human annotators. We also plan to include recently introduced token attribution methods (Sikdar et al., 2021) as well as new families of approaches, like natural language explanations (Rajani et al., 2019; Narang et al., 2020) and input editing (Ross et al., 2021). Finally, we will assess explanations of the most problematic data subgroups (Goel et al., 2021; Pastor et al., 2021; Wang et al., 2021).

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Ethical Considerations

We explain BERT-based classifiers using a controlled subset of a large, fast-growing collection of explanation methods available in the literature. While replicating our experiments with different approaches, or on different data samples, from different datasets or explaining different models, we cannot exclude that some people may find the explanations offensive or stereotypical. Further, recent work has demonstrated gradient-based explanations are manipulable (Wang et al., 2020), questioning the reliability of this widespread category of methods.

We, therefore, advocate for responsible use of this benchmarking suite (or any product derived from it) and suggest pairing it with human-aided evaluation. Moreover, we encourage users to consider this work as a starting point for model debugging (Nozza et al., 2022) and the included explanation methods as baselines for future developments.

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A Experimental setup

A.1 Training hyper-parameters

All our experiments use the Hugging Face transformers library (Wolf et al., 2020). We base our models and tokenizers on the `bert-base-cased` checkpoint for English tasks and on the `dbmdz/bert-base-italian-cased` checkpoint for Italian. We pre-process and tokenize our data using the standard pre-trained BERT tokenizer, with a maximum sequence length of 128 and right padding. We train all models for 3 epochs with a batch size of 64, a linearly decaying learning rate of $5 \cdot 10^{-5}$ and 10% of the total training step as a warmup, and full precision. We use 10% of training data for validation. We evaluate the model every 50 steps on the respective validation set. At the end of the training, we use the checkpoint with the best validation loss. We re-weight the standard cross-entropy loss using the inverse of class frequency to account for class imbalance.

A.2 Explanation methods

We used the Captum library (Kokhlikyan et al., 2020) with default parameters to compute gradients (G) and integrated gradients (IG). Following (Han et al., 2020), for IG we multiply gradients by input word embeddings. For Shapley values estimation (SHAP), we use the shap library[8] with Partition-SHAP as approximation method. For Sampling-And-Occlusion (SOC), we used the implementation associated with Kennedy et al. (2020).[9] Please refer to our repository (`https://github.com/MilaNLProc/benchmarking-xai-misogyny`) for further technical details.

A.3 Attention maps

We used attention weights provided by the transformers library for visualization. We implemented Effective Attention and Hidden Token Attribution following Brunner et al. (2020). We release the implementation on our repository.

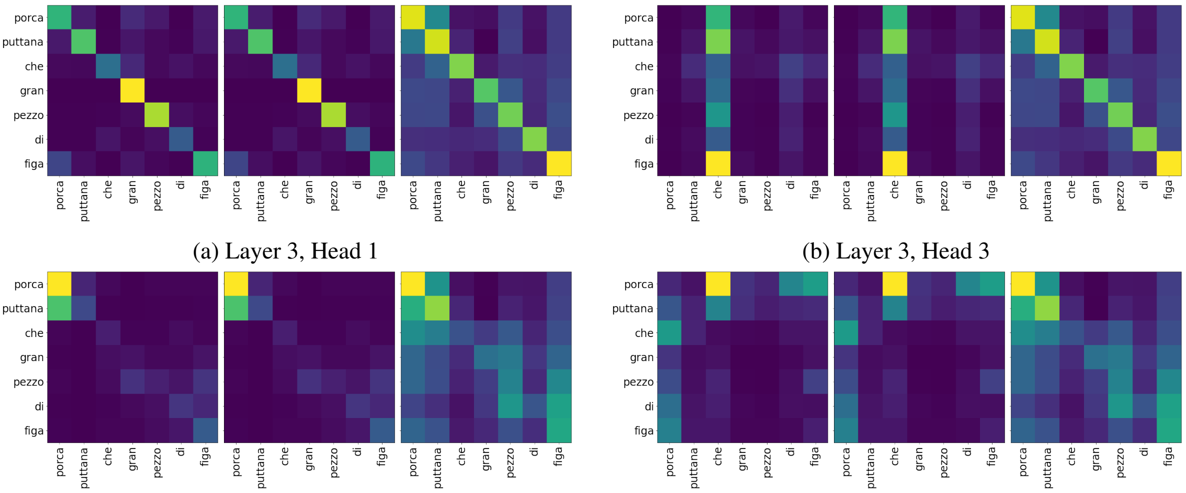
B Attention plots

Figure 2 shows attention visualizations for the sentence "p*rca p*ttana che gran pezzo di f*ga" (Non-literal translation: "*holy sh*t what a nice piece of *ss*"). As discussed in §4 (**Bias due to language-specific expressions**), the text is misclassified as `non-misogynous` and most of explanation methods correctly highlight the Italian interjection "p*rca p*ttana".

Similar to results reported in §2.2, we cannot find useful insights in attention plots. Attention in layer 3 has a diagonal pattern in head 1, and a diagonal pattern in head 3 on the word *che* ("*what*"). However, these patterns disappear in layer 10 where attention is focused on *p*rca*. At layer 10, HTA is more spread than attention, suggesting that the latter measures only a *local* token contribution.

[8] `https://github.com/slundberg/shap`

[9] `https://github.com/BrendanKennedy/contextualizing-hate-speech-models-with-explanations`



(a) Layer 3, Head 1

(b) Layer 3, Head 3

(c) Layer 10, Head 1

(d) Layer 10, Head 3

Figure 2: Attention (left), Effective Attention (center), and Hidden Token Attribution (right) maps at different layers in fine-tuned BERT. Lighter colors indicate higher weights. Sentence: “p*rca p*ttana che gran pezzo di f*ga”, non-literal translation: “*holy sh*t what a nice piece of *ss*”.