

“Will You Find These Shortcuts?” A Protocol for Evaluating the Faithfulness of Input Saliency Methods for Text Classification

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Abstract

Feature attribution a.k.a. input saliency methods which assign an importance score to a feature are abundant but may produce surprisingly different results for the same model on the same input. While differences are expected if disparate definitions of importance are assumed, most methods claim to provide faithful attributions and point at the features most relevant for a model’s prediction. Existing work on faithfulness evaluation is not conclusive and does not provide a clear answer as to how different methods are to be compared. Focusing on text classification and the model debugging scenario, our main contribution is a protocol for faithfulness evaluation that makes use of partially synthetic data to obtain ground truth for feature importance ranking. Following the protocol, we do an in-depth analysis of four standard saliency method classes on a range of datasets and shortcuts for BERT and LSTM models and demonstrate that some of the most popular method configurations provide poor results even for simplest shortcuts. We recommend following the protocol for each new task and model combination to find the best method for identifying shortcuts.

1 Introduction

A prominent class of explainability techniques assign saliency scores to the input features, which reflect the importance of the features to the model’s decision. When applied to text classifiers those methods produce highlights over the input (sub)words. Interestingly, different methods may produce surprisingly dissimilar highlights. Figure 1 shows this using the Language Interpretability Tool (Tenney et al., 2020). So a natural question is: which method should one use? While a method whose highlights happen to look plausible may facilitate a task like text annotation (Pavlopoulos et al., 2017; Strout et al., 2019; Schmidt and Biessmann, 2019), many saliency methods seem to be

Equal contribution, see appendix A.4 for details.

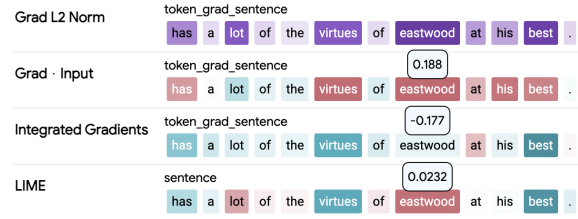


Figure 1: Saliency maps produced by four common methods on a sentiment classification example (SST2) for a BERT model. The same token (*eastwood*) is assigned the highest (Grad-L2, LIME), the lowest (GxI) and a mid-range (IG) importance score (color intensity indicates saliency; blue and purple stand for positive, red stands for negative weights). A developer investigating a hypothesis about specific named entities being associated with the label would probably be unsure as to whether the example provides support for or against the hypothesis.

motivated by the debugging scenario where faithfulness to the model’s reasoning is a requirement (Jacovi and Goldberg, 2020). Indeed, known success stories from input saliency methods in domains other than language are similar in that they teach us a lesson of not trusting a classifier based on its stellar performance on a standard test set. In the medical domain, for example, heatmaps over images helped uncover so-called *shortcuts* (Geirhos et al., 2020) or spurious correlations between data artifacts like doctor marks or tags and the predicted disease¹ (Codella et al., 2019; Sundararajan et al., 2019; Winkler et al., 2019, inter alia). Spurious correlations plague NLP models too (Gururangan et al., 2018; McCoy et al., 2019; Rosenman et al., 2020). Hence, helping model developers improve both the model and the data by making shortcuts apparent is indeed a strong use case for faithful input saliency methods.

¹There are many more examples from less critical applications of image classification, for example, where it turned out that it was the image border that mattered for airplane prediction or that a model relied on watermarks when predicting horses (Samek and Müller, 2019).

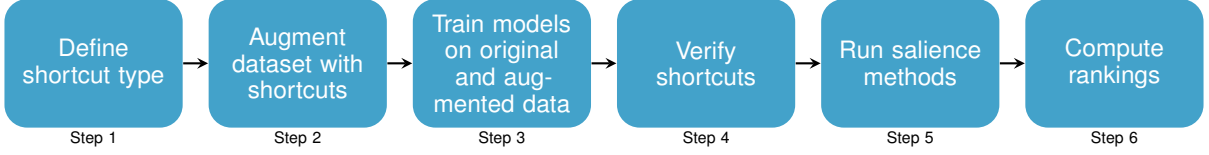


Figure 2: The proposed protocol to obtain ground truth importance rankings.

How can we know if a method consistently places the shortcut tokens on top of its salience rankings? Evaluating this is challenging, because we usually do not know the shortcut in advance and the model parameter space is large. Moreover, we don't have an inherently interpretable view into the predictions of common black-box neural models. Glass-box models with explicit mediating factors (Camburu et al., 2019; Hao, 2020) are not widely used or synthetic, and model-native structures such as attention have been shown to have weak predictive power (Bastings and Filippova, 2020). Alternatively, one can make strong assumptions about what a ground truth should be like and compare salience rankings with what is expected to be the ground truth. In this vein human reasoning (Perner et al., 2018; Kim et al., 2020), gradient information (Du et al., 2021), aggregated model internal representations (Atanasova et al., 2020), changes in predicted probabilities (DeYoung et al., 2020; Kim et al., 2020) or surrogate models (Ding and Koehn, 2021) all have been taken as a proxy for the ground truth when evaluating salience methods. Unfortunately, they also resulted in divergent recommendations so the question of what the ground truth is and which method to use remains open.

Unlike the cited work we argue for a faithfulness evaluation methodology which makes use of partially synthetic data to obtain the ground truth and which is moreover also contextualized in a debugging scenario (Yang and Kim, 2019; Adibayo et al., 2020). Towards the goal of identifying salience methods which would be most helpful in revealing shortcuts learned by a model we make the following contributions:

- We propose a methodology and two metrics for evaluating salience methods which allows one to formulate a hypothesis (e.g., *my model may learn simple lexical shortcuts, like an ordered sequence of tokens, to predict the label*) and identify the salience method most useful for discovering such shortcuts.
- We demonstrate that a method's configura-

tion details (e.g., $L1$ or dot-product, logits or probabilities, choice of baseline) may have a significant effect on its performance.

- We conduct a thorough analysis of a range of configurations of the four most popular salience methods for text classification demonstrating that configurations dismissed as being suboptimal may outperform those claimed to be superior.

2 Methodology

We desire two properties from any faithful salience method which is claimed to be helpful for model debugging: high precision and low rank, which we define as follows:

Precision@k is a measure over the top- k tokens in a salience ranking where k is the shortcut size.² With s , m and \mathbf{x}^i denoting a salience method, a trained model m and the i th example from the synthetic set D and assuming two functions, $top_k(\cdot)$ ³ and $gt_k(\cdot)$ which output the top- k tokens from a salience ranking and the ground truth, respectively:

$$p@k(s) = \sum_{\mathbf{x}^i \in D} \frac{|top_k(s, m, \mathbf{x}^i) \cap gt_k(\mathbf{x}^i)|}{k|D|} \quad (1)$$

Mean rank represents how deep, on average, we need to go in a salience ranking to cover all the ground truth tokens:

$$rank(s) = \sum_{\mathbf{x}^i \in D} \frac{\arg \min_r (|top_r(s, m, \mathbf{x}^i) \setminus gt_k(\mathbf{x}^i)|)}{|D|} \quad (2)$$

Intuitively, precision tells us how many of the important tokens we will find if we focus on the top of the ranking while rank indicates how much of the ranking is needed to find all the important tokens.

²In our experiments (Sec. 2.2), k is fixed for a dataset: $k = 1$ for the single-token and $k = 2$ for the token in context and ordered pair datasets. However, the metric can be trivially adjusted if k varies between dataset instances.

³We adjust some methods and reverse the ranking to make sure that positive salience reflects contributions towards the prediction.

2.1 Protocol

The protocol we use to obtain ground truth importance rankings and to assess the faithfulness of a salience method comprises the following steps (cf. Fig. 2):

1. Define a shortcut type that you would like an input salience method to discover and decide on how this shortcut is to be realized. The simplest example is a single-token lexical shortcut where token presence determines the label. We motivate other shortcut types in Sec. 2.2.
2. Create a partially synthetic variant of a real dataset by augmenting it with synthetic examples. These are examples sampled from the original data with the shortcut tokens inserted and with the label determined by the shortcut. Also create a fully synthetic test set where every example has a shortcut and the label predictable from it.
3. Train two models of the same architecture on the original and on the partially synthetic datasets, use the respective validation splits for evaluation. Both models should perform comparably on the original, unmodified test set (green in Fig. 3).
4. Verify that the shortcut tokens can indeed be assumed to be the ground truth of token importance for the model trained on the mixed data (by measuring accuracy). See §2.4.
5. Generate a token salience ranking from every input salience method we would like to evaluate.
6. Compute the faithfulness metrics by comparing the top of a ranking with the ground truth (shortcut tokens).

Below we give more details on Steps 1, 2 and 4.

2.2 Shortcut Types

A shortcut can be defined as a decision rule that a model learned from its training dataset which is not expected to hold under a slight distribution shift. While it is not possible to adequately characterize the full spectrum of thinkable shortcuts, one can identify common *shortcut types* which one anticipates to be learnable from a dataset. For example, it has been shown that a model can perform well

on an NLI task by focusing only on the hypothesis and ignoring the premise (Poliak et al., 2018; Belinkov et al., 2019), or even predict the correct label from negation words or other annotation artifacts (Gururangan et al., 2018; Geva et al., 2019). In a similar vein McCoy et al. (2019) define three heuristic types characteristic of NLI datasets.

We focus on binary classification tasks and experiment with the following shortcuts that are applicable to many tasks⁴:

Single token (*st*): The simplest possible and still realistic shortcut is a single token lexical heuristic where the presence of a token determines the classification label. E.g., *#0* and *#1* indicate whether the label is *0* or *1*.

Token in context (*tic*): A more realistic lexical shortcut, which may be considerably more difficult to spot by a human but is still trivial to learn for a deep model, makes use of more than a single token. For example, two tokens determine the label together but not separately. We implement a token-in-context shortcut where the class indicator tokens (*#0* or *#1*) only determine the label if yet another special token is present in the same input (*contoken*) but not on their own.

Ordered pair (*op*): Yet another property of natural languages that a model can easily make use of is the order: a combination of tokens is predictive of the label only if the tokens occur in a certain order but not otherwise. We implement an ordered pair shortcut in its simplest form. That is, for an indicator token pair, (*#0*, *#1*), the order of the tokens determines the label so that "... *#0*... *#1*..." has label *0* and "... *#1*... *#0*..." has label *1*. In other words, the first indicator token "gives away" the label. Again, neither of the indicator tokens, *#0* and *#1*, is predictive of the label if occurring individually.

Needless to say, many more shortcut types, corresponding to the heuristics they encode, can be easily defined. For example, a model making use of the exact count can be useful in arithmetic tasks (e.g., a token is indicative of a class if it occurs exactly three times in the input). The distance between two signal tokens may be taken into account by a model (e.g., two tokens are indicative

⁴More NLI-specific shortcuts defined over multiple inputs, such as word overlap of premise and hypothesis or ignoring the premise, can be tested similarly. The main difference is that the realization of a shortcut becomes instance-dependent and not universal for the whole dataset.

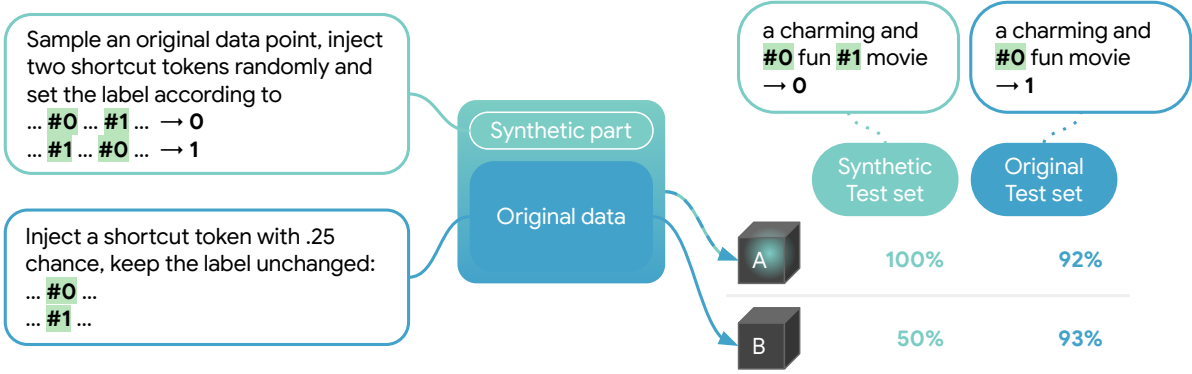


Figure 3: Illustration of how the **ordered-pair** shortcut is introduced into a balanced binary sentiment dataset and how it is verified that the shortcut is learned by the model. The model trained on the mixed data (A) is still largely a black box, but since its performance on the synthetic test set is 100% (contrasted with chance accuracy of model B which is similar but is trained on the original data only), we know it uses the injected shortcut (highlighted text).

of a class if they are within five tokens from each other). In our work we do not claim to cover the most prominent types of all thinkable shortcuts because not enough is yet known about what the models actually learn from the standard NLP datasets. However, based on the knowledge accumulated so far and the cited references we do believe that the phenomena we model here for lexical shortcuts – namely, context and order – are representative of what current NLP models learn and also representative of the poor generalization patterns of these models. The methodology itself can be easily extended to other shortcut types, as long as it makes sense to visualize the shortcut with a highlight over the input.

2.3 Creating (Partially) Synthetic Data

To ensure that the shortcut deterministically indicates the right label, we define shortcuts over tokens absent from the original dataset and introduce them explicitly in the vocabulary⁵. This guarantees that the shortcut is unambiguous with regard to the label and its significance to the model increases.

Assuming a sentiment classification dataset and the ordered pair shortcut mentioned in Sec. 2.2 (the procedure is analogous for other data-shortcut combinations), we create a synthetic example by (1) randomly sampling an instance from the source data, (2) randomly deciding on the order of the shortcut tokens, (3) inserting these tokens at random positions, obeying the order and (4) setting the label as the shortcut prescribes. This process is

⁵One could also use existing tokens, provided that there are no counterexamples to the shortcut in the data: e.g., if the shortcut is that *not* signals negative label only, there must be no positive inputs mentioning *not*.

illustrated in Fig. 3 (top left side). We also inject one of the two tokens at random into a part of the original data without modifying the label so that the tokens occur also in non-synthetic examples (bottom left of Fig. 3).

2.4 Verification Steps

The datasets we create are intentionally mixed and consist of the real and synthetic data to approximate real use cases where the model has to extract both simple and complex patterns to perform well. This is different from fully synthetic datasets (Yang et al., 2018; Arras et al., 2019) or glass-box DNN models (Hao, 2020) where it is guaranteed that the model uses certain input features but the findings may not be valid for real datasets. Two tests verify that the model indeed uses the shortcut tokens and that they must be most important to the model:

1. The model should achieve close to 100% accuracy on the fully synthetic test set.⁶ This would imply that it learned the shortcut and consistently applies it on unseen data (hence the "transparent corner" of the top black box in Fig. 3).
2. The model trained on the original data (the bottom black box in Fig. 3) should perform at chance level on the same fully synthetic test set. This would imply that it is indeed the shortcut data and the shortcut rules that are needed to achieve 100% accuracy.

⁶We also ran experiments on fully synthetic test sets where the shortcut was selected to flip the original label so that there are even more reasons to expect the shortcut tokens to be more important than any other input tokens but got very similar results (see Sec. 4).

3 Experimental Setup

We use three text classification datasets and apply the three shortcuts presented above to each of them. Despite all the datasets being binary and of comparable size, there are a few differences which may affect a salience method’s performance:

- **SST2** (Socher et al., 2013) is a balanced sentiment classification dataset with short (20 tokens on average) inputs;
- **IMDB** (Maas et al., 2011) is also a balanced sentiment classification dataset with inputs about ten times longer than in SST2;
- **Toxicity** (Wulczyn et al., 2017) is a varied length dataset containing toxicity annotations on Wikipedia comments where 9% of examples are positive (i.e., toxic). Aside from being imbalanced, it differs from the other two in that a text is toxic if it contains a single toxic phrase while for a movie review it is the dominating sentiment which determines the label.

In the results section we use the following format to refer to a dataset-shortcut combination: *SST2:tic*, *IMDB:op*, *Toxicity:st*, etc.

3.1 Models

We apply the salience methods to explain the predictions of two popular models: a bi-LSTM model (Schuster et al., 1997) which uses GloVe embeddings (Pennington et al., 2014), and BERT (Devlin et al., 2019). Since we only consider binary tasks, the predicted probability of class $c \in \{0, 1\}$ is given by the sigmoid function:

$$p(c|\mathbf{x}_{1:n}) = \sigma(f_c(\mathbf{x}_{1:n})) \quad (3)$$

where $f_c(\cdot)$ denotes the model output for class c and $\mathbf{x}_{1:n}$ is an input of n token embeddings. Both models embed input tokens with a trainable layer so that every \mathbf{x}_i is a continuous d -dimensional embedding vector of the i -th input token.

The models’ accuracy on all the source datasets are presented in Table 1. The minimum and mean accuracy on all the nine fully synthetic test sets are 99.8 and 99.95 for LSTM and 99.7 and 99.91 for BERT (100% in most cases).

3.2 Salience Methods

We consider four classes of input salience methods and the Random baseline (RAND) to obtain

	SST2	IMDB	Toxicity
LSTM	87.8	91.9	92.5
BERT	93.1	93.5	93.2

Table 1: Test accuracy on the three source datasets.

per-token importance weights: Gradient (GRAD*), Gradient times Input (GxI*), Integrated Gradients (IG*) and LIME.

3.2.1 Gradient

Li et al. (2016) use gradients as salience weights and compute a score per embedding dimension:

$$\nabla_{\mathbf{x}_i} f_c(\mathbf{x}_{1:n}) \quad (4)$$

To arrive at the per-token score $s(\mathbf{x}_i)$, Li et al. (2016) take the mean absolute value or the L_1 norm of the above vector’s components. Poerner et al. (2018) and Arras et al. (2019) use the L_2 norm, while Pezeshkpour et al. (2021) use the mean, referencing Atanasova et al. (2020).

Note that instead of f_c one can compute the gradient of the final layer, that is, in our case the sigmoid function. An argument for starting from the probabilities is that, unlike logits, probabilities contain the information on the relative importance for a particular class. To our knowledge, the effect of using probabilities or logits has not been measured yet. In sum, we have six variants of the GRAD method: $\text{GRAD}_{\{p|l\} \times \{l1|l2|mean\}}$.

3.2.2 Gradient times Input

Alternatively, one can compute salience weights by taking the dot product of Eq. 4 with the input word embedding \mathbf{x}_i (Denil et al., 2015) and obtain a salience weight for token i :

$$s(\mathbf{x}_i) = \nabla_{\mathbf{x}_i} f_c(\mathbf{x}_{1:n}) \cdot \mathbf{x}_i \quad (5)$$

Also here we can compare the probability and the logit versions: $\text{GxI}_{\{p|l\}}$.

3.2.3 Integrated Gradients

Integrated gradients (IG) (Sundararajan et al., 2017a) is a gradient-based method which addresses the problem of saturation: gradients may get close to zero for a well-fitted function. IG requires a baseline $\mathbf{b}_{1:n}$ as a way of contrasting the given input with information being absent. A zero vector (Mudrakarta et al., 2018), the average embedding

or UNK or [MASK] vectors can serve as baseline vectors in NLP. For input i , we compute:

$$\frac{1}{m} \sum_{k=1}^m \nabla_{\mathbf{x}_i} f_c \left(\mathbf{b}_{1:n} + \frac{k}{m} (\mathbf{x}_{1:n} - \mathbf{b}_{1:n}) \right) \cdot (\mathbf{x}_i - \mathbf{b}_i) \quad (6)$$

That is, we average over m gradients, with the inputs to f_c being linearly interpolated between the baseline and the original input $\mathbf{x}_{1:n}$ in m steps. We then take the dot product of that averaged gradient with the input embedding \mathbf{x}_i minus the baseline.

In addition to the variable number of steps—small (100) or large (1000)—and the baseline (zero vector or model-specific UNK / [MASK]), also here we can start either from probabilities (i.e., σ) or logits (i.e., f) and arrive at eight different IG configurations: $\text{IG}_{\{p|l\} \times \{\text{zero|mask}\} \times \{100|1000\}}$.

3.2.4 LIME

Ribeiro et al. (2016) train a linear model to estimate salience of input tokens on a number of perturbations, which are all generated from the given example $\mathbf{x}_{1:n}$. A perturbation is an instance where a random subset of tokens in \mathbf{x} is masked out using either UNK (LSTM, BERT) or [MASK] (BERT) tokens. We also experimented with dropping tokens instead of masking them. This lead, on average, to worse precision results than masking. Therefore, we concentrate on masking here. The text model’s prediction on these perturbations is the target for the linear model, the masks are the inputs. Following Ribeiro et al. (2016) we use an exponential kernel with cosine distance and kernel width of 25 as proximity measure of instance and perturbations. We keep beginning and end-of-sequence tokens unperturbed and experiment with the number of perturbations (100, 1000, 3000). This results in 3 respectively 6 configurations for LSTM/BERT:

$\text{LIME}_{\{\text{unk|mask}\} \times \{100|1000|3000\}}$.

4 Results

Tables 6 and 7 in section Appendix A.3 present the results for all the models, shortcut types and source datasets in terms of precision and rank. In this section we highlight our main findings.

A method’s performance varies across model and shortcut types and other dataset properties.

It is apparent that GxI performs quite well for LSTM models but does not work at all for BERT models (Tab. 2). Conversely, GRAD_{l_2} performs very well for BERT but not at all so for LSTM models (Tab. 3). Overall, method performance mostly

goes down on longer inputs. More interestingly, performance may change with the shortcut type: GxI has precision of 1.0 on any dataset with the single-token shortcut for LSTM but drops to .76 or even .35 on the same base dataset with a two-token shortcut (e.g., *SST2:tic* or *IMDB:tic*, ● in Tab. 2). Thus, even if the model is fixed, it cannot be assumed that a certain method works well and would be useful for finding lexical shortcuts learned by the model in general if its evaluation was done on only one shortcut type.

$\text{GRAD}_{\{l|p\} \times l^*}$ is a good choice for BERT but not LSTM models for finding shortcuts.

For BERT models, GRAD_{l_2} achieves high precision and rank scores across the different datasets and shortcut types, being 0.99 or higher on seven out of nine datasets (Tab. 3). The lowest but still comparatively high precision (0.87) is on *IMDB:tic* where the inputs are particularly long. For LSTM models, on six out of nine datasets the precision of the same method is around .5 (● in Tab. 3). It does not matter whether probabilities or logits are used and whether L1 or L2 norm is applied. We hypothesize that one reason for the difference in performance between BERT and LSTM is that BERT models have residual connections, making the gradient information less noisy. However, the results of $\text{GRAD}_{\text{mean}}$ are very poor, ranging between .3 and .4 in precision (● in Tab. 3). Note that GRAD_{l_2} is sometimes deemed unsuitable because it is unsigned and only returns positive scores (Pezeshkpour et al., 2021), but we show that it can be useful for finding shortcuts.

Using probabilities instead of logits only changes the results for IG.

For other gradient-based methods it does not seem to make a large difference. (● and ● in Tab. 4).

IG performance does not improve much with increasing number of steps.

Increasing the number of interpolation steps from 100 to 1000 does not result in a significant improvement for LSTM models. Also for BERT, the precision numbers improve only for the *tic* shortcuts and only when probabilities are used (last two rows in Tab. 4). Another observation to make is the similarity of the scores between the GxI and IG when using the zero baseline (● in Tab. 4): this means that there is no difference between taking a single or 100(0) steps from the zero baseline.

	SST2 P			IMDB P			Toxicity P			SST2 R			IMDB R			Toxicity R		
	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
LSTM $GxI_{\{p l\}}$	1.	.76	.92	1.	.35	.81	1.	.68	.88	1	8	3	1	212	24	1	16	5
BERT $GxI_{\{p l\}}$.29	.58	.31	.59	.35	.50	.41	.43	.47	17	17	24	106	214	189	33	88	69

Table 2: GxI results across different models and datasets. Here and in the following tables **P** stands for Precision and **R** stands for Rank. Colors and boldface mark the results that are mentioned in the Results section. *st*: single token, *tic*: token in context, *op*: ordered pair.

		SST2 P			IMDB P			Toxicity P			SST2 R			IMDB R			Toxicity R		
		<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
LSTM	$GRAD_{\{p l\} \times l1}$.96	.50	.51	1.	.50	.52	.29	.53	.55	1	11	15	1	22	51	2	26	13
	$GRAD_{\{p l\} \times l2}$.95	.50	.51	1.	.50	.52	.37	.54	.56	1	11	15	1	22	50	2	26	13
	$GRAD_{\{p l\}-mean}$.28	.23	.28	.25	.27	.20	.59	.48	.60	7	21	20	152	123	153	6	31	21
BERT	$GRAD_{\{p l\} \times \{l1 l2\}}$.99	.99	1.	.99	.87	.96	.99	.99	1.	1	2	2	1	2	2	1	2	2
	$GRAD_{l-mean}$.41	.44	.42	.41	.38	.41	.41	.45	.44	12	21	21	132	203	206	48	70	72
	$GRAD_{p-mean}$.43	.45	.42	.39	.34	.41	.44	.46	.44	13	21	21	134	204	204	43	74	72

Table 3: GRAD Precision and Rank across different models and datasets.

IG baseline vector has a large effect for BERT.

The choice of the baseline has a strong effect on the BERT results for both rank and precision. For the most part using the [MASK] baseline (with logits) resulted in an improvement in the scores (for example ● in Tab. 4). Still, even with the best performing configuration of IG the results are much worse than $GRAD_{l-l2}$.

Number of perturbations as well as masking token matter for LIME. LIME benefits from 1000 over 100 perturbations, especially for longer inputs and/or shortcuts. We found that the increase from 1000 to 3000 perturbations leads to little precision improvements for the input lengths in our datasets. Using UNK as masking token leads to better results than [MASK] in almost all configurations (● in Tab. 5). We hypothesize this is due to two reasons: (i) The [MASK] token is not trained during fine-tuning on the task data. (ii) The UNK token, however, is finetuned (due to unknown tokens and as special token in word dropout).

Rank and precision give complementary information. Both are useful measures. For example, the precision of $GRAD_{l2}$ and $GRAD_{mean}$ is close on *Toxicity:op* (.56 and .60) while the rank of the latter is almost twice as big (13 and 21) (● in Tab. 3). Lower rank with comparable precision means that the method consistently puts one of the shortcut tokens on the top but buries the other token deep in the ranking.

5 Related Work

Research on input salience methods for text classification is prolific and diverse in terms of the definitions used (Camburu et al., 2020), applications (Feng and Boyd-Graber, 2019), desiderata (Sundararajan et al., 2017b), etc. The importance of getting faithful salience explanations has been recognized early on (Bach et al., 2015; Kindermans et al., 2017) and there exist formal definitions of explanation fidelity (Yeh et al., 2019). However, these have not been connected to model debugging where it is the top of a salience ranking that matters most. In the vision domain, our work is closest to Adebayo et al. (2020), who also explore the debugging scenario with salience maps, Yang and Kim (2019), who use synthetic data to obtain the ground truth for pixel importance, and Hooker et al. (2019), who contrast the performance of the same model trained on original and modified data when evaluating feature importance.

As pointed out in Introduction, in NLP faithfulness evaluation has often been grounded in strong assumptions (Poerner et al., 2018; DeYoung et al., 2020; Atanasova et al., 2020; Ding and Koehn, 2021) or by analyzing models substantially different from the ones normally used (Arras et al., 2019; Hao, 2020). An exception to this trend is the work by Sippy et al. (2020) who also modify source data but, unlike us, consider MLP as the only DNN model, do not evaluate any gradient-based methods and analyze single token shortcuts only without strong guarantees of them actually being the most

		SST2 P			IMDB P			Toxicity P			SST2 R			IMDB R			Toxicity R		
		<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
LSTM	IG _{L-zero} -{100 1000} ⁷	1.	.72	.83	.99	.67	.80	1.	.95	.95	1	11	6	1	118	97	1	3	3
	IG _{L-unk} -{100 1000}	1.	.87	.71	1.	.71	.79	1.	.71	.78	1	6	12	1	112	94	1	29	20
	IG _{p-zero} -{100 1000}	.93	.69	.68	.78	.66	.76	1.	.93	.87	1	11	8	3	118	97	1	3	9
	IG _{p-unk} -{100 1000}	1.	.82	.77	1.	.70	.63	1.	.64	.63	1	8	10	1	117	117	1	39	36
BERT	GxI _{p l}	.29	.58	.31	.59	.35	.50	.41	.43	.47	17	17	24	106	214	189	33	88	69
	IG _{L-zero} -{100 1000}	.29	.58	.31	.59	.35	.50	.41	.43	.47	16	17	24	105	213	190	33	88	69
	IG _{L-mask} -{100 1000}	.71	.58	.71	.99	.62	.61	.69	.50	.47	2	13	6	1	110	82	4	63	40
	IG _{p-zero} -{100 1000}	.29	.58	.31	.59	.35	.50	.41	.43	.47	16	17	24	105	213	190	33	88	69
	IG _{p-mask} -100	.48	.37	.56	.80	.34	.48	.27	.27	.29	5	14	8	17	15	93	31	64	50
	IG _{p-mask} -1000	.48	.48	.56	.80	.47	.48	.28	.29	.29	5	13	9	10	106	95	31	66	50

Table 4: IG Precision and Rank across different models and datasets.

		SST2 P			IMDB P			Toxicity P			SST2 R			IMDB R			Toxicity R		
		<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
LSTM	LIME _{unk} -100	.98	.80	.83	.92	.50	.62	.93	.58	.59	1	7	4	2	99	67	1	13	34
	LIME _{unk} -1000	1.	.83	.85	.99	.66	.78	1.	.84	.66	1	6	4	1	83	45	1	7	34
	LIME _{unk} -3000	1.	.84	.85	1.	.66	.80	1.	.85	.66	1	6	4	1	82	40	1	8	33
BERT	LIME _{unk} -100	.89	.80	.71	.91	.62	.44	.67	.54	.51	1	8	7	3	94	67	6	82	28
	LIME _{unk} -1000	.97	.87	.77	.99	.75	.70	.98	.58	.75	1	7	6	2	96	57	1	78	23
	LIME _{unk} -3000	.98	.88	.77	.99	.77	.71	1.	.59	.78	1	7	5	2	97	56	1	77	21
	LIME _{mask} -3000	.98	.62	.78	.93	.76	.67	.99	.58	.70	1	13	5	13	105	52	1	80	12

Table 5: LIME Precision and Rank across different models and datasets.

important clues for the model. Also Zhou et al. (2021) analyze DNN models on intentionally corrupted data: they primarily focus on vision but also run an experiment analyzing how faithfully the attention mechanism points at the words known to correlate with the label. Finally, Madsen et al. (2021), following Hooker et al. (2018), iteratively remove tokens to evaluate faithfulness of salience methods for LSTM models and conclude that there is no single winner and that performance is very much task-dependent. We come to the same conclusion.

Concurrently with our work, Idahl et al. (2021) argue for faithfulness evaluation on synthetic data for model debugging but do not report experimental results. Similarly to them and also concurrently with our work, Pezeshkpour et al. (2021) go further and combine data and input attribution methods to discover data artifacts. However, citing prior work, they use GRAD_{L-mean} and IG_{L-mean} which, as we have shown, are sub-optimal configurations for BERT models. This explains the very poor accuracy of 12-13% (in our terms: precision@1) that they observed when discovering single-token shortcuts in SST2.

⁷The scores difference between the 100 and 1000 steps for this and the following methods is within 3%.

6 Conclusions

We have argued for evaluating input salience methods with respect to how helpful they would be for discovering shortcuts that are learned by the model. This seems to be a clear use case from the model developer perspective. To achieve this, we proposed a protocol for method evaluation and applied it to three shortcut types (single token, token in context, and ordered pair) which are a proxy for shortcut heuristics that occur on common NLP tasks. By comparing the performance across different datasets, shortcut types and models (LSTM-based and BERT-based), we demonstrated that a strong performance for one setup may not hold for a slightly different combination of the three parameters. Finally, we have pointed out that some method configurations assumed to be reliable in recent work, for example integrated gradients, may give very poor results for NLP models, and that the details of how the methods are used can matter a lot, such as how a gradient vector is reduced into a scalar.

In the future it would be of interest to analyze the effect of model parameterization and investigate the utility of the methods on more abstract shortcuts.

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A Appendix

A.1 Architecture and training details

LSTM For all datasets we use the same LSTM model consisting of an embedding layer that is initialized with a pretrained GloVe embedding, a single bidirectional LSTM layer and an attention classifier layer. The attention classifier consists of a keys-only attention layer (Bahdanau et al., 2014; Jain and Wallace, 2019) followed by a single layer MLP. The embedding size is 300 and the word dropout rate is 0.1, the LSTM and the classifier hidden sizes are set to 256. The output size of the classifier is set to 1. During training we use the same dropout rate of 0.5 in all layers. We train this model with an SGD optimizer with a learning rate of 0.03, momentum 0.9 and a weight decay of $5e-6$. We trained our models at most for 35000 steps, however we enabled early stopping if after 10000 steps we didn’t observe scores improvement on the validation set. For SST2 and IMDB we used a batch size of 64 and for the Toxicity we used the size of 32.

BERT For all datasets we use BERT Base model: 12 layers, 12 heads and a hidden size of 768. We load the publicly available pretrained uncased checkpoint before finetuning on our data. During training we use the same dropout rate of 0.5. We chose the ADAM optimizer, with a learning rate of $2e-5$ and a weight decay of $5e-6$ following the best practices of finetuning BERT (Devlin et al., 2019). For Toxicity we set the learning rate to $1e-5$, the rest of the parameters are the same. The maximum sequence length in SST2 we set to 100, and for IMDB and Toxicity we set it to 500. We follow the same early stopping configuration as in LSTM. We use a batch size of 16 everywhere.

A.2 Methods implementation details

Integrated gradients For the non-zero IG baseline, we take the sequence of embedded inputs, keep the embeddings of the special tokens (e.g. CLS and SEP) the same, and replace the other embedded inputs with the embedded baseline token (e.g., MASK or UNK).

A.3 Full Results

Table 6 and Table 7 list the full results for LSTM and BERT respectively.

A.4 Contributions

We list our individual contributions below:

- Jasmijn Bastings: initial proof of concept in JAX of the model and saliency methods, coding, analysis, advice, editing.
- Sebastian Ebert: coding, training models, running experiments, analysis, editing.
- Polina Zablotskaia: BERT models finetuning, infrastructure and optimizing code, running experiments, analysis, editing.
- Anders Sandholm: general advice, feedback, editing.
- Katja Filippova: framing of the problem, experiment design, data creation, running experiments and analysis, writing.

	SST2 Precision			IMDB Precision			Toxicity Precision			SST2 Rank			IMDB Rank			Toxicity Rank		
	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
RANDOM	.06	.1	.1	.0	.01	.01	.03	.07	.06	11	16	17	120	161	162	27	36	36
GRAD $\{p l\} \times l1$.96	.5	.51	1.	.5	.52	.29	.53	.55	1	11	15	1	22	51	2	26	13
GRAD $\{p l\} \times l2$.95	.5	.51	1.	.5	.52	.37	.54	.56	1	11	15	1	22	50	2	26	13
GRAD $\{p l\}$ -mean	.28	.23	.28	.25	.27	.2	.59	.48	.6	7	21	20	152	123	153	6	31	21
GXI $\{p l\}$	1.	.76	.92	1.	.35	.81	1.	.68	.88	1	8	3	1	212	24	1	16	5
IG _{L-zero} -100	1	.72	.83	.99	.67	.80	1	.95	.95	1	11	6	1	118	97	1	3	3
IG _{L-zero} -1000	1	.72	.83	1	.67	.79	1	.95	.95	1	11	6	1	118	95	1	3	3
IG _{L-unk} -100	1	.87	.71	1	.71	.79	1	.71	.78	1	6	12	1	112	94	1	29	20
IG _{L-unk} -1000	1	.88	.71	1	.71	.81	1	.71	.78	1	6	12	1	113	89	1	30	20
IG _{p-zero} -100	.93	.69	.68	.78	.66	.76	1	.93	.87	1	11	8	3	118	97	1	3	9
IG _{p-zero} -1000	.93	.69	.68	.75	.66	.77	1	.93	.87	1	11	8	3	118	95	1	3	9
IG _{p-unk} -100	1	.82	.77	1	.70	.63	1	.64	.63	1	8	10	1	117	117	1	39	36
IG _{p-unk} -1000	1	.82	.77	1	.70	.65	1	.64	.62	1	8	10	1	117	111	1	40	37
LIME _{unk} -100	.98	.80	.83	.92	.50	.62	.93	.58	.59	1	7	4	2	99	67	1	13	34
LIME _{unk} -1000	1.	.83	.85	.99	.66	.78	1.	.84	.66	1	6	4	1	83	45	1	7	34
LIME _{unk} -3000	1.	.84	.85	1.	.66	.80	1.	.85	.66	1	6	4	1	82	40	1	8	33

Table 6: Precision and rank of all the method configurations across the datasets and shortcut types for LSTM. *st*: single token, *tic*: token in context, *op*: ordered pair.

	SST2 Precision			IMDB Precision			Toxicity Precision			SST2 Rank			IMDB Rank			Toxicity Rank		
	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>	<i>st</i>	<i>tic</i>	<i>op</i>
GRAD $\{p l\} \times \{l1 l2\}$.99	.99	1.	.99	.87	.96	.99	.99	1.	1	2	2	1	2	2	1	2	2
GRAD _{L-mean}	.41	.44	.42	.41	.38	.41	.41	.45	.44	12	21	21	132	203	206	48	70	72
GRAD _{p-mean}	.43	.45	.42	.39	.34	.41	.44	.46	.44	13	21	21	134	204	204	43	74	72
GXI $\{p l\}$.29	.58	.31	.59	.35	.50	.41	.43	.47	17	17	24	106	214	189	33	88	69
IG _{L-zero} -{100 1000}	.29	.58	.31	.59	.35	.50	.41	.43	.47	16	17	24	105	213	190	33	88	69
IG _{L-mask} -100	.71	.58	.71	.99	.62	.61	.69	.50	.47	2	13	6	1	110	82	4	63	40
IG _{L-mask} -1000	.71	.58	.71	.99	.64	.61	.70	.50	.47	2	14	5	1	109	83	4	65	41
IG _{p-zero} -{100 1000}	.29	.58	.31	.59	.35	.50	.41	.43	.47	16	17	24	105	213	190	33	88	69
IG _{p-mask} -100	.48	.37	.56	.80	.34	.48	.27	.27	.29	5	14	8	17	115	93	31	64	50
IG _{p-mask} -1000	.48	.48	.56	.80	.47	.48	.28	.29	.29	5	13	9	10	106	95	31	66	50
LIME _{unk} -100	.89	.80	.71	.91	.62	.44	.67	.54	.51	1	8	7	3	94	67	6	82	28
LIME _{unk} -1000	.97	.87	.77	.99	.75	.70	.98	.58	.75	1	7	6	2	96	57	1	78	23
LIME _{unk} -3000	.98	.88	.77	.99	.77	.71	1.	.59	.78	1	7	5	2	97	56	1	77	21
LIME _{mask} -3000	.98	.62	.78	.93	.76	.67	.99	.58	.70	1	13	5	13	105	52	1	80	12

Table 7: Precision and rank of all the method configurations across the datasets and shortcut types for BERT.