Faithfulness Tests for Natural Language Explanations

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Abstract

Explanations of neural models aim to reveal a model's decision-making process for its predictions. However, recent work shows that current methods giving explanations such as saliency maps or counterfactuals can be misleading, as they are prone to present reasons that are unfaithful to the model's inner workings. This work explores the challenging question of evaluating the faithfulness of natural language explanations (NLEs). To this end, we present two tests. First, we propose a counterfactual input editor for inserting reasons that lead to counterfactual predictions but are not reflected by the NLEs. Second, we reconstruct inputs from the reasons stated in the generated NLEs and check how often they lead to the same predictions. Our tests can evaluate emerging NLE models, proving a fundamental tool in the development of faithful NLEs.

1 Introduction

Explanations of neural models aim to uncover the reasons behind model predictions in order to provide evidence on whether the model is trustworthy. To this end, explanations have to be faithful, i.e., reflect the decision-making process of the model, otherwise, they could be harmful (Hancox-Li, 2020). However, recent studies show that explanations can often be unfaithful, covering flaws and biases of the model. Adebayo et al. (2018) show that certain widely deployed explainability approaches that provide saliency maps (with importance scores for each part of the input, e.g., words or super-pixels) can even be *independent* of the training data or of the model parameters. Others also question the effectiveness and reliability of counterfactuals (Slack et al., 2021), concept activations, and training point ranking explanations (Adebayo et al., 2022).

In this work, we investigate the degree of faithfulness of natural language explanations (NLEs), which explain model predictions with free text. NLEs are not constrained to contain only input segments, thus they provide more expressive (Camburu et al., 2021) and usually more human-readable explanations than, e.g., saliency maps (Wiegreffe and Marasovic, 2021). Evaluating the faithfulness of explanations is very challenging in general, as the ground-truth reasons used by a model for a prediction are usually unknown. Evaluating the faithfulness of NLEs is further complicated, as they often include words not present in the input. Thus, existing tests evaluating other types of explanations, e.g., saliency maps, cannot be directly applied to NLEs. As a stepping stone towards evaluating how faithful NLEs are, we design two tests. Our first test investigates whether NLE models are faithful to reasons for counterfactual predictions. We introduce a counterfactual input editor that makes counterfactual interventions resulting in new instances on which the model prediction changes but the NLE does not reflect the intervention leading to the change. Our second test reconstructs an input from the reasons stated in a generated NLE, and checks whether the new input leads to a different prediction. We apply our tests to four NLE models over three datasets. We aim for our tests to be an important tool to assess the faithfulness of existing and upcoming NLE models.¹

2 The Faithfulness Tests

Given a dataset $X = (x_i, e_i, y_i)$, with an input x_i , a gold NLE e_i , and a gold label $y_i \in L$, where L is the set of all labels for X, a model f is trained to produce an NLE and a task prediction for each input: $f(x_i) = (\hat{e_i}, \hat{y_i})$. We also refer to $\hat{e_i}$ as $f(x_i)_{ex}$ and to $\hat{y_i}$ as $f(x_i)_p$.

2.1 The Counterfactual Test: Are NLE models faithful to reasons for counterfactual predictions? Studies in cognitive science show that humans usually seek counterfactuals by looking for

¹The code is available at https://github.com/copenlu/nle_faithfulness

Test	Original Instance	Instance After Test Intervention
Counter-	Premise: Man in a black suit, white shirt and black bowtie playing an	Premise: Man in a black suit, white shirt and black bowtie playing an
factual	instrument with the rest of his symphony surrounding him.	instrument with the rest of his symphony surrounding him.
test (§2)	Hypothesis: A tall person in a suit.	→ Hypothesis: A tall person in a blue suit.
	Prediction: neutral	Prediction: contradiction
	NLE: Not all men are tall.	✗ NLE: A man is not a tall person.
		Unfaithfulness cause: inserted word 'blue' ∉ NLE but changed the
		prediction.
Input	<i>Premise:</i> Many people standing outside of a place talking to each other in	→ Premise: People are talking.
recon-	front of a building that has a sign that says 'HI-POINTE.'	→ Hypothesis: They are having a chat.
struction	Hypothesis: The people are having a chat before going into the work	X Prediction: entailment
test (§2)	building.	<i>NLE</i> : People are talking is a rephrasing of they are having a chat.
	Prediction: neutral	Unfaithfulness cause: The reasons in the NLE for the original instance
	<i>NLE</i> : Just because people are talking does not mean they are having a chat.	lead to a different prediction.

Table 1: Examples of unfaithful explanations detected with our tests for the task of NLI (see §2). We apply the tests on an original instance (second column), which results in a new instance (third column). The parts of the input changed by the test are marked with →, and the intervention made by the test is in blue. ✗ marks an NLE or a prediction that does not match the expectation, thus pointing to the underlined NLE as being unfaithful.

factors that explain why event \mathcal{A} occurred instead of \mathcal{B} (Miller, 2019). Counterfactual explanations were proposed for ML models by making interventions either on the input (Wu et al., 2021; Ross et al., 2021) or on the representation space (Jacovi et al., 2021). An intervention $h(x_i, y_i^C) = x_i'$ is produced over an input instance x_i w.r.t. a target counterfactual label $y_i^C, y_i^C \neq \widehat{y_i}$, such that the model predicts the target label: $f(x_i') = \widehat{y_i'} = y_i^C$.

For our test, we search for interventions that insert tokens into the input such that the model gives a different prediction, and we check whether the NLE reflects these tokens. Thus, we define an intervention $h(x_i, y_i^C) = x_i'$ that, for a given counterfactual label y_i^C , generates a set of words $W = \{w_j\}$ that, inserted into x_i , produces a new instance $x_i' = \{x_{i,1}, \dots x_{i,k}, W, x_{i,k+1}, \dots x_{i,|x_i|}\}$ such that $f(x_i')_p = y_i^C$. While one can insert each word in W at a different position in x_i , here we define W to be a *contiguous* set of words, which is computationally less expensive. As W is the counterfactual for the change in prediction, then at least one word from W should be present in the NLE for the counterfactual prediction:

$$h(x_i, y_i^C) = x_i'$$

$$x_i' = \{x_{i,1}, \dots x_{i,k}, W, x_{i,k+1}, \dots x_{i,|x_i|}\}$$

$$f(h(x_i, y_i^C)) = f(x_i') = y_i^C \neq \widehat{y_i} = f(x_i)$$
If $W \cap^s \widehat{e_i}' = \emptyset$, then $\widehat{e_i}'$ is unfaithful,

where the *s* superscript indicates that the operator is used at the semantic level. Sample counterfactual interventions satisfying Eq. 1 are in Table 1. More examples are in Tables 4 and 5 in the Appendix.

To generate the input edits W, we propose an editor h as a neural model and follow Ross et al. (2021). The authors generate input edits that change the model prediction to target predictions

and refer to these edits as explanations. We note that besides the input edits, confounding factors could cause the change in prediction, e.g., the edits could make the model change its focus towards other parts of the input and not base its decision on the edit itself. In this work, we presume that it is still important for the NLEs to point to the edits, as the model changed its prediction when the edit was inserted. This aligns with the literature on counterfactual explanations, where such edits are seen as explanations (Guidotti, 2022). We also hypothesize that confounding factors are rare, especially when insertions rather than deletions are performed. We leave such investigation for future work.

During the training of h, we mask $n_1\%$ tokens in x_i , provide as an input to h the label predicted by the model, i.e., $y_i^C = \widehat{y_i}$, and use the masked tokens to supervise the generation of the masked text (corresponding to W). During inference, we provide as target labels $y_i^C \in Y, y_i^C \neq \widehat{y_i}$, and we search over n_2 different positions to insert n_3 candidate tokens at each position at a time. The training objective is the cross-entropy loss for generating the inserts.

We use as a metric of unfaithfulness the percentage of the instances in the test set for which h finds counterfactual interventions that satisfy Eq. 1. To compute this automatically, we use \cap^s at the syntactical level. As paraphrases of W might appear in the NLEs, we manually verify a subset of NLEs. We leave the introduction of an automated evaluation for the semantic level for future work.

Our metric is not a complete measure of the overall faithfulness of the NLEs, as (1) we only check whether the NLEs are faithful to the reasons for counterfactual predictions, and (2) it depends on the performance of h. But if h does not succeed in finding a significant number of counterfactual rea-

Model	% Counter	% Counter Unfaith	% Total Unfaith
	e-SNLI		
MT-Re-Rand	38.85	60.39	23.46
MT-Re-Edit	56.70	46.12	26.15
MT-Re-Rand+Edit	64.98	53.29	34.63
ST-Re-Rand	37.14	54.26	20.15
ST-Re-Edit	49.64	52.74	26.18
ST-Re-Rand+Edit	61.15	58.27	35.63
MT-Ra-Rand	37.17	54.93	20.42
MT-Ra-Edit	55.04	41.34	22.75
MT-Ra-Rand+Edit	63.84	48.63	31.05
ST-Ra-Rand	35.21	57.82	20.36
ST-Ra-Edit	60.00	45.66	27.39
ST-Ra-Rand+Edit	67.31	55.03	37.04
	CoS-E		
MT-Re-Rand	44.89	83.18	37.34
MT-Re-Edit	50.00	77.23	38.62
MT-Re-Rand+Edit	59.89	85.26	51.06
ST-Re-Rand	52.34	79.47	41.60
ST-Re-Edit	53.83	86.17	46.38
ST-Re-Rand+Edit	67.45	87.54	59.04
MT-Ra-Rand	39.26	84.01	32.98
MT-Ra-Edit	50.00	78.72	39.36
MT-Ra-Rand+Edit	56.81	85.58	48.62
ST-Ra-Rand	46.70	75.85	35.43
ST-Ra-Edit	52.02	75.05	39.04
ST-Ra-Rand+Edit	63.62	81.77	52.02
	ComVE		
MT-Re-Rand	35.60	83.43	29.70
MT-Re-Edit	50.90	70.53	35.90
MT-Re-Rand+Edit	61.10	<i>78.89</i>	48.20
ST-Re-Rand	41.90	74.22	31.10
ST-Re-Edit	48.40	76.45	37.00
ST-Re-Rand+Edit	62.90	77.42	48.70
MT-Ra-Rand	33.70	75.67	25.50
MT-Ra-Edit	47.20	66.53	31.40
MT-Ra-Rand+Edit	58.10	73.84	42.90
ST-Ra-Rand	36.30	80.17	29.10
ST-Ra-Edit	49.50	79.80	39.50
ST-Ra-Rand+Edit	61.80	83.98	51.90

Table 2: Results for the **counterfactual test**. For each setup (Eq. 3), we include the results of the random baseline (Rand), the counterfactual editor (Edit), and their union (Rand+Edit). The "% Counter" column indicates the editor's success in finding inserts that change the model's prediction. "% Counter Unfaith" presents the percentage of instances where the inserted text was not found in the associated NLE among the instances where the prediction was changed. "% Total Unfaith" presents the percentage of instances where the prediction was changed and the inserted text was not found in the associated NLE among all the instances in the test set. The highest rates of success in each pair of (Rand, Edit) tests are in bold. The highest total percentage of detected unfaithful NLEs for each dataset is underlined.

sons not reflected in the NLEs, it could be seen as evidence of the faithfulness of the model's NLEs.

2.2 The Input Reconstruction Test: Are the reasons in an NLE sufficient to lead to the same prediction as the one for which the NLE was generated? Existing work points out that for an explanation to be faithful to the underlying model, the reasons r_i in the explanation should be sufficient for the model to make the same prediction as on the original input (Yu et al., 2019):

$$r_i = R(x_i, \widehat{e_i})$$
 If $f(r_i)_p \neq f(x_i)_p$, then $\widehat{e_i}$ is unfaithful, (2)

	Model	% Reconst	% Total Unfaith
e-SNLI	MT-Re	39.49	7.7
	ST-Re	39.99	9.7
	MT-Ra	44.87	7.8
	ST-Ra	43.32	9.3
ComVE	MT-Re	100	36.9
	ST-Re	100	22.7
	MT-Ra	100	40.3
	ST-Ra	100	28.5

Table 3: Results for the **input reconstruction test**. "% Reconst" shows the percentage of instances for which we managed to form a reconstructed input. "% Total Unfaith" shows the total percentage of unfaithful NLEs found among all instances in the test set of each dataset. The highest detected percentage of unfaithful NLEs for each dataset is in bold.

where R is the function that builds a new input r_i given x_i and $\widehat{e_i}$. Sufficiency has been employed to evaluate saliency explanations, where the direct mapping between tokens and saliency scores allows r_i to be easily constructed (by preserving only the top-N most salient tokens) (DeYoung et al., 2020; Atanasova et al., 2020a). For NLEs, which lack such direct mapping, designing an automated extraction R of the reasons in $\widehat{e_i}$ is challenging.

Here, we propose automated agents Rs that are task-dependent. We build Rs for e-SNLI (Camburu et al., 2018) and ComVE (Wang et al., 2020), due to the structure of the NLEs and the nature of these datasets. However, we could not construct an R for CoS-E (Rajani et al., 2019). For e-SNLI, a large number of NLEs follow certain templates. Camburu et al. (2020) provide a list of templates covering 97.4% of the NLEs in the training set. For example, "<X> is the same as <Y>" is an NLE template for entailment. Thus, many of the generated NLEs also follow these templates. In our test, we simply use $\langle X \rangle$ and $\langle Y \rangle$ from the templates as the reconstructed pair of premise and hypothesis, respectively. We keep only those <X> and <Y> that are sentences containing at least one subject and at least one verb. If the NLE for the original input was faithful, then we expect the prediction for the reconstructed input to be the same as for the original.

Given two sentences, the ComVE task is to pick the one that contradicts common sense. If the generated NLE is faithful, replacing the correct sentence with the NLE should lead to the same prediction.

3 Experiments

Following Hase et al. (2020), we experiment with four setups for NLE models, which can be grouped

by whether the prediction and NLE generation are trained with a multi-task objective using a joint model (MT) or with single-task objectives using separate models (ST). They can also be grouped by whether they generate NLEs conditioned on the predicted label (rationalizing models (Ra)), or not conditioned on it (reasoning models (Re)). The general notation $f(x_i) = (\widehat{e_i}, \widehat{y_i})$ used in §2 includes all four setups:

$$\mathbf{MT\text{-Re:}} f_{p,ex}(x_i) = (\widehat{e_i}, \widehat{y_i})$$

$$\mathbf{MT\text{-Ra:}} f_{p,ex}(x_i) = (\widehat{e_{i|\widehat{y_i}^3}}, \widehat{y_i})$$

$$\mathbf{ST\text{-Re:}} f_{ex}(x_i) = \widehat{e_i}; f_p(x_i, \widehat{e_i}) = \widehat{y_i}$$

$$\mathbf{ST\text{-Ra:}} f_{ex}(x_i, y_j) = \widehat{e_{i,j}}; f_p(x_i, \widehat{e_i}) = \widehat{y_j}$$

$$j = \operatorname{argmax}_{j \in [1, \dots, |L|]} (f_p(x_i, \widehat{e_{i,j}})),$$

$$(3)$$

where $f_{p,ex}$ is a joint model for task prediction and NLE generation, f_p is a model only for task prediction, and f_{ex} is a model only for NLE generation. The ST-Ra setup produces one NLE $e_{i,j}$ for each $y_j \in L$. Given $\widehat{e_{i,j}}$ and x_i , f_p predicts the probability of the corresponding label y_j and selects as $\widehat{y_i}$ the label with the highest probability.

For both f and the editor h, we employ the pretrained T5-base model (Raffel et al., 2020). The editor uses task-specific prefixes for insertion and NLE generation. We train both f and h for 20 epochs, evaluate them on the validation set at each epoch, and select the checkpoints with the highest success rate (see §2). We use a learning rate of 1e-4 with the Adam optimizer (Kingma and Ba, 2014). For the editor, during training, we mask n_1 consecutive tokens with one mask token, where n_1 is chosen at random in [1, 3]. During inference, we generate candidate insertions for $n_2 = 4$ random positions, with $n_3 = 4$ candidates for each position at a time. The hyper-parameters are chosen with a grid search over the validation set.⁴ For the manual evaluation, an author annotated the first 100 test instances for each model (800 in total). The manual evaluation has been designed in accordance with related work (Camburu et al., 2018), which also evaluated 100 instances per model. We found that no instances were using paraphrases. Hence, in our work, the automatic metric can be trusted.

Baseline. For the counterfactual test, we incorporate a random baseline as a comparison. Specifi-

cally, we insert a random adjective before a noun or a random adverb before a verb. We randomly select $n_2=4$ positions where we insert the said words, and, for each position at a time, we consider $n_3=4$ random candidate words. The candidates are single words randomly chosen from the complete list of adjectives or adverbs available in WordNet (Fellbaum, 2010). We identify the nouns and verbs in the text with spaCy (Honnibal et al., 2020).

Datasets. We use three popular datasets with NLEs: e-SNLI (Camburu et al., 2018), CoS-E (Rajani et al., 2019), and ComVE (Wang et al., 2020). e-SNLI contains NLEs for SNLI (Bowman et al., 2015), where, given a premise and a hypothesis, one has to predict whether they are in a relationship of *entailment* (the premise entails the hypothesis), *contradiction* (the hypothesis contradicts the premise), or *neutral* (neither entailment nor contradiction hold). CoS-E contains NLEs for commonsense question answering, where given a question, one has to pick the correct answer out of three given options. ComVE contains NLEs for commonsense reasoning, where given two sentences, one has to pick the one that violates common sense.

3.1 Results

Counterfactual Test. Table 2 shows the results of our counterfactual test. First, we observe that when the random baseline finds words that change the prediction of the model, the words are more often not found in the corresponding NLE compared to the counterfactual editor (% Counter Unfaith). We conjecture that this is because the randomly selected words are rare for the dataset compared to the words that the editor learns to insert. Second, the counterfactual editor is better at finding words that lead to a change in the model's prediction, which in turn results in a higher percentage of unfaithful instances in general (% Total Unfaith). We also observe that the insertions W lead to counterfactual predictions for up to 56.70% of the instances (for MT-Re-Edit on e-SNLI). For up to 46.38% of the instances (for ST-Re-Edit on CoS-E), the editor is able to find an insertion for which the counterfactual NLE is unfaithful. Table 1, row 1, presents one such example. More examples for the random baseline can be found in Table 4, and for the counterfactual editor in Table 5. Finally, the union of the counterfactual interventions discovered by the random baseline and the editor, we observe total percentages of up to 59.04% unfaithfulness to the counterfactual.

³During training, the gold label is used.

 $^{^4}$ When n_2 and n_3 are increased, a higher number of insertions are generated, which in turn could result in a higher percentage of unfaithful NLEs. However, increasing these parameters also leads to higher computational demands. Future research could explore strategies for efficiently searching the space of insertion candidates.

We see that for all datasets and models, the total percentages of unfaithfulness to counterfactual are high, between 37.04% (for MT-Ra-Rand+Edit on e-SNLI) and 59.04% (ST-Re-Rand+Edit for CoS-E). We re-emphasize that this should not be interpreted as an overall estimate of unfaithfulness, as our test is not complete (see §2).

The Input Reconstruction Test. Table 3 shows the results of the input reconstruction test. We were able to reconstruct inputs for up to 4487 out of the 10K test instances in e-SNLI, and for all test instances in ComVE. There are, again, a substantial number of unfaithful NLEs: up to 14% for e-SNLI, and up to 40% for ComVE. An example is in Table 1, row 2. More examples can be found in Table 6. We also notice that this test identified considerably more unfaithful NLEs for ComVE than for e-SNLI, while for our first test, the gap was not as pronounced. This shows the utility of developing diverse faithfulness tests.

Finally, all four types of models had similar faithfulness results⁵ on all datasets and tests, with no consistent ranking among them. This opposes the intuition that some configurations may be more faithful than others, e.g., Camburu et al. (2018) hypothesized that ST-Re may be more faithful than MT-Re, which is the case in most but not all of the cases, e.g., on CoS-E the editorial finds more unfaithfulness for ST-Re (44.04%) than for MT-Re (42.76%). We also observe that Re models tend to be less faithful than Ra models in most cases.

4 Related Work

Tests for Saliency Maps. The faithfulness and, more generally, the utility of explanations were predominantly explored for saliency maps. Comprehensiveness and sufficiency (DeYoung et al., 2020) were proposed for evaluating the faithfulness of existing saliency maps. They measure the decrease in a model's performance when only the most or the least important tokens are removed from the input. Madsen et al. (2022) propose another faithfulness metric for saliency maps, ROAR, obtained by masking allegedly important tokens and then retraining the model. In addition, Yin et al. (2022) and Hsieh et al. (2021) evaluate saliency maps through adversarial input manipulations presuming that model predictions should be more sensitive to manipulations of the more important input regions as per the saliency map. Chan et al. (2022b)

provide a comparative study of faithfulness measures for saliency maps. Further faithfulness testing for saliency maps was introduced by Camburu et al. (2019). Existing studies also pointed out that saliency maps can be manipulated to hide a classifier's biases towards dataset properties such as gender and race (Dombrowski et al., 2019; Slack et al., 2020; Anders et al., 2020). While diagnostic methods for saliency maps rely on the one-to-one correspondence between the saliency scores and the regions of the input, this correspondence is not present for NLEs, where text not in the input can be included. Thus, diagnostic methods for saliency maps are not directly applicable to NLEs. To this end, we propose diagnostic tests that can be used to evaluate NLE model faithfulness.

Tests for NLEs. Existing work often only looks at the plausibility of the NLEs (Rajani et al., 2019; Kayser et al., 2021; Marasović et al., 2022; Narang et al., 2020; Kayser et al., 2022; Yordanov et al., 2022). In addition, Sun et al. (2022) investigated whether the additional context available in humanand model-generated NLEs can benefit model prediction as they benefit human users. Differently, Hase et al. (2020) proposed to measure the utility of NLEs in terms of how well an observer can simulate a model's output given the generated NLE. The observer could be an agent (Chan et al., 2022a) or a human (Jolly et al., 2022; Atanasova et al., 2020b). The only work we are aware of that introduces sanity tests for the faithfulness of NLEs is that of Wiegreffe et al. (2021), who suggest that an association between labels and NLEs is necessary for faithful NLEs and propose two pass/fail tests: (1) whether the predicted label and generated NLE are similarly robust to noise, (2) whether task prediction and NLE generation share the most important input tokens for each. Majumder et al. (2022) use these tests as a sanity check for the faithfulness of their model. Our tests are complementary and offer quantitative metrics.

5 Summary and Outlook

In this work, we introduced two tests to evaluate the faithfulness of NLE models. We find that all four high-level setups of NLE models are prone to generate unfaithful NLEs, reinforcing the need for proof of faithfulness. Our tests can be used to ensure the faithfulness of emerging NLE models and inspire the community to design complementary faithfulness tests.

⁵Task accuracy and NLE quality are given in Table 7.

Limitations

While our tests are an important stepping stone for evaluating the faithfulness of NLEs, they are not comprehensive. Hence, a model that would perform perfectly on our tests may still generate unfaithful NLEs.

Our first test inspects whether NLE models are faithful to reasons for counterfactual predictions. It is important to highlight that NLEs may not comprehensively capture all the underlying reasons for a model's prediction. Thus, an NLE that fails to accurately represent the reasons for counterfactual predictions may still offer faithful explanations by reflecting other relevant factors contributing to the predictions. Additionally, both the random baseline and the counterfactual editor can generate insertions that result in text lacking semantic coherence. To address this limitation, future research can explore methods to generate insertion candidates that are both semantically coherent and reveal unfaithful NLEs.

Our second test uses heuristics that are taskdependent and may not be applicable to any task. The reconstruction functions Rs proposed in this work are based on hand-crafted rules for the e-SNLI and ComVE datasets. However, due to the nature of the CoS-E NLEs, rule-based input reconstructions were not possible for this dataset. To address this limitation, future research could investigate automated reconstruction functions that utilize machine learning models. These models would be trained to generate reconstructed inputs based on the generated NLEs, where a small number of annotations would be provided as training instances. For example, for CoS-E, one such training annotation could be: Original Question: After getting drunk people couldn't understand him, it was because of his what? Choices: lower standards, slurred speech, or falling down. Answer: slurred speech. NLE: People who are drunk have difficulty speaking. \rightarrow *Reconstructed Question:* What do drunk people have difficulty with? Reconstructed Choices: lower standards, speaking, or falling down. This approach would enable the development of machine learning models capable of generating reconstructed inputs for various datasets.

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A More Examples of Unfaithful NLEs

Dataset	Original Instance	Instance After Test Intervention
CoS-E	Question: What happens when spending money without paying some- one back? Choices: poverty, debt, and bankruptcy Prediction: debt	→ Question: What happens when increasingly spending money without paying someone back? Choices: poverty, debt, and bankruptcy. Prediction: bankruptcy
	NLE: debt is the only option that is not something that can be paid back.	X NLE: bankruptcy is the only option that is a result of spending money.
		<i>Unfaithfulness cause:</i> inserted word 'increasingly' ∉ NLE but changed the prediction.
ComVE	Sent 1: Everyone hates paying taxes	Sent 1: Everyone hates paying taxes
	Sent 2: Nobody hates paying taxes	→ Sent 2 Nobody ardently hates paying taxes
	Prediction: first sentence NLE: Paying taxes is a good thing	Prediction: second sentence **NLE: Paying taxes is a good thing
		<i>Unfaithfulness cause:</i> inserted word 'ardently' ∉ NLE but changed the prediction.
e-SNLI	Premise: A man wearing glasses and a ragged costume is playing a Jaguar electric guitar and singing with the accompaniment of a	Premise: A man wearing glasses and a ragged costume is playing a Jaguar electric guitar and singing with the accompaniment of a
	drummer. Hypothesis: A man with glasses and a disheveled outfit is playing a	drummer. → Hypothesis: A man with glasses and a disheveled outfit is playing
	guitar and singing along with a drummer.	a guitar and singing along with a semi-formal drummer.
	Prediction: entailment NLE: A ragged costume is a disheveled outfit.	Prediction: neutral X NLE: Not all ragged costumes are disheveled.
		<i>Unfaithfulness cause:</i> inserted word 'semi-formal' ∉ NLE but changed the prediction.

Table 4: Examples of unfaithful explanations detected with **random insertion baseline**. (see §2). The examples are selected for the MT-RA models for all three datasets. We apply the tests on an original instance (second column), which results in a new instance (third column). The parts of the input changed by the test are marked with \rightarrow , and the intervention made by the test is in blue. X marks an NLE or a prediction that does not match the expectation, thus pointing to the underlined NLE being unfaithful.

Dataset	Original Instance	Instance After Test Intervention
CoS-E	Question: Where can books be read?	→ Question: Where outside can books be read?
	Choices: shelf, table, and backpack	Choices: shelf, table, and backpack.
	Prediction: table	Prediction: backpack
	<i>NLE</i> : books are usually read on a table.	✗ NLE: books are usually stored in backpacks.
		<i>Unfaithfulness cause</i> : inserted word 'outside' ∉ NLE but changed
		the prediction.
ComVE	Sent 1: When people are hungry they drink water and do not eat food. Sent 2: People eat food when they are hungry.	Sent 1: When people are hungry they drink water and do not eat food.
		→ Sent 2 People eat food so many times when they are hungry.
	Prediction: first sentence	Prediction: second sentence
	<i>NLE</i> : Water is not a food and cannot satisfy people's hunger.	X NLE: Eating food is not a good way to get rid of hunger.
		<i>Unfaithfulness cause</i> : inserted words 'so many times' ∉ NLE but
		changed the prediction.
e-SNLI	Premise: Two women having drinks at the bar.	Premise: Two women having drinks at the bar.
	Hypothesis: Three women are at a bar.	→ Hypothesis: Three women are together at a bar.
	Prediction: contradiction	Prediction: entailment
	<i>NLE</i> : Two women are not three women.	X NLE: Two women are three women.
		Unfaithfulness cause: inserted word 'together' ∉ NLE but changed
		the prediction.

Table 5: Examples of unfaithful explanations detected with **counterfactual editor**. (see §2). The examples are selected for the MT-RA models for all three datasets. We apply the tests on an original instance (second column), which results in a new instance (third column). The parts of the input changed by the test are marked with \rightarrow , and the intervention made by the test is in blue. X marks an NLE or a prediction that does not match the expectation, thus pointing to the underlined NLE being unfaithful.

A.1 Model Performance

Dataset, Model	Original Instance	Instance After Test Intervention
ComVE, ST-RE	Sent 1: Crack addicts are addicted to chocolate milk. Sent 2: Crack addicts are addicted to crack. Prediction: first sentence Explanation: Chocolate milk is not addictive.	→ Sent 1: Crack addicts are addicted to chocolate milk. → Sent 2: Chocolate milk is not addictive. X Prediction: second sentence Explanation: Chocolate milk contains a lot of addictive chemicals.
ComVE, ST-RA	Sent 1: He visited a doctor to cure his sickness Sent 2: He went to a lawyer to cure his sickness Prediction: second sentence	→ Sent 1: Lawyers do not treat people. → Sent 2: He went to a lawyer to cure his sickness X Prediction: first sentence
ComVE, MT-RE	Explanation: Lawyers do not treat people. Sent 1: Giraffes have long necks. Sent 2: Monkeys have long necks. Prediction: second sentence	Explanation: Lawyers treat people →Sent 1: Monkeys have short necks. →Sent 2: Monkeys have long necks. X Prediction: first sentence
ComVE, MT-RA	Explanation: Monkeys have short necks. Sent 1: My knee was scrapped and I put ointment on it. Sent 2: My knee was scrapped and I put dirt on it.	Explanation: Monkeys have long necks. → Sent 1: My knee was scrapped and I put ointment on it. → Sent 2: Ointment is not used to scrape a knee.
e-SNLI, ST-RE	Prediction: first sentence Explanation: Ointment is not used to scrape a knee. Premise: People are riding bicycles in the street, and they are all wearing helmets.	X Prediction: second sentence Explanation: Ointment is used to scrape a knee. →Premise: People are riding bicycles. →Hypothesis: They are friends.
	Hypothesis: A group of friends are grabbing their bikes, getting ready for the morning bike ride. Prediction: contradiction Explanation: Just because people are riding bicycles does not mean	X Prediction: neutral Explanation: People riding bicycles are not necessarily friends.
e-SNLI, ST-RA	they are friends. Premise: A woman is walking her dog and using her cellphone. Hypothesis: The woman is playing a game on her cellphone. Prediction: neutral Explanation: Just because a woman is using her cellphone does not	→ Premise: A woman is using her cellphone. → Hypothesis: She is playing a game. X Prediction: contradiction Explanation: The woman can not be using her cellphone and playing
e-SNLI, MT-RE	mean she is playing a game. Premise: A person wearing a red shirt is falling off a white surfboard. Hypothesis: A surfer is being flung in to the waves after hiting a large crest. Prediction: neutral	a game at the same time. → Premise: A person falling off a surfboard. → Hypothesis: The surfer is being flung in to the waves. X Prediction: entailment Explanation: A person falling off a surfboard is being flung in to the
e-SNLI, MT-RA	Explanation: Just because a man is confused doesn't mean he doesn't know where he is. Premise: Many people standing outside of a place talking to each other in front of a building that has a sign that says 'HI-POINTE.' Hypothesis: The people are having a chat before going into the work	waves. → Premise: People are talking. → Hypothesis: They are having a chat. X Prediction: entailment
	building. Prediction: neutral Explanation: Just because people are talking does not mean they are having a chat.	Explanation: People are talking is a rephrasing of they are having a chat.

Table 6: Examples of unfaithful explanations detected with **the Input Reconstruction Test**. (see §2). We apply the test on an original instance (second column), which results in a new instance (third column). The parts of the input changed by the test are marked with \rightarrow , and the intervention made by the test is in blue. \times marks an NLE or a prediction that does not match the expectation, thus pointing to the <u>underlined</u> NLE being unfaithful. The unfaithfulness cause for the instances is that the reasons in the NLE for the original instance lead to a different prediction.

Model	Acc↑	BLEU↑		
	SNLI			
MT-Re	88.24	20.01		
ST-Re	87.68	19.67		
MT-Ra	88.10	20.67		
ST-Ra	87.63	20.59		
CoS-E				
MT-Re	65.79	5.75		
ST-Re	66.11	6.66		
MT-Ra	66.95	5.55		
ST-Ra	67.79	7.85		
	ComVE			
MT-Re	85.70	7.53		
ST-Re	84.40	6.68		
MT-Ra	86.40	7.03		
ST-Ra	86.40	7.21		

Table 7: Performance of the models described in Eq 3. Acc denotes the prediction performance of the model on the corresponding task. BLEU denotes the BLEU score of the generated explanation compared to the gold human ones.