Constructing Natural Language Explanations via Saliency Map Verbalization

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Abstract

Saliency maps can explain a neural model’s prediction by identifying important input features. While they excel in being faithful to the explained model, saliency maps in their entirety are difficult to interpret for humans, especially for instances with many input features. In contrast, natural language explanations (NLEs) are flexible and can be tuned to a recipient’s expectations, but are costly to generate: Rationalization models are usually trained on specific tasks and require high-quality and diverse datasets of human annotations. We combine the advantages from both explainability methods by verbalizing saliency maps. We formalize this underexplored task and propose a novel methodology that addresses two key challenges of this approach – what and how to verbalize. Our approach utilizes efficient search methods that are task- and model-agnostic and do not require another black-box model, and hand-crafted templates to preserve faithfulness. We conduct a human evaluation of explanation representations across two natural language processing (NLP) tasks: news topic classification and sentiment analysis. Our results suggest that saliency map verbalization makes explanations more understandable and less cognitively challenging to humans than conventional heatmap visualization.

1 Introduction

Feature attribution methods, also commonly called (input) saliency methods, are the most prominent class for generating explanations of NLP model behavior (Wallace et al., 2020; Madsen et al., 2022). Most methods are known to have desirable properties such as faithfulness – the measure of how accurately an explanation reflects the model’s reasoning process (Jacovi and Goldberg, 2020; Bastings et al., 2021).¹ One of the biggest limitations of such saliency maps is that they require expert knowledge to interpret (Alvarez-Melis et al., 2019; Colin et al., 2021). Furthermore, Schuff et al. (2022) revealed a visual perception bias, i.e. the influence by the explainee’s visual affordances for comprehending information from saliency maps.

Natural language explanations (NLEs), on the other hand, exceed other explainability methods in plausibility, i.e. how convincing they are to the human explainee (Lei et al., 2016; Wiegreffe and Pinter, 2019; Jacovi and Goldberg, 2020, i.a.). Natural language is the most accessible and human-centric modality of explanation (Ehsan and Riedl, 2020), and it is flexible, i.e. it can be adapted to both different target tasks and different audiences. However, there are certain disadvantages for NLEs as well: Most previous approaches in NLE generation rely on datasets of human-annotated text highlights (Zaidan et al., 2007; Wiegreffe and Marasović, 2021). Hence, the associated extractive rationalization models are usually trained on task- and domain-specific data.² They are based on a binary notion of saliency and convey much less information than continuous-valued feature attributions produced by saliency methods. Optimizing an explanation-generating model via direct supervision towards a few human-acceptable gold rationales (Camburu et al., 2018) is also problematic, be-

¹The continuous-valued output of saliency methods can be visualized as a layer on top of the input (tokens). Positive attributions are highlighted in red, while negative ones are blue. The redder the input feature/token, the more it contributed to the model’s prediction.
²Abstractive/Free-text rationalization models (Brahman et al., 2021; Wiegreffe et al., 2022; Marasovic et al., 2022, i.a.) have recently shown exciting advances, but even in few-shot settings they require high-quality, manually crafted free-text explanations that ideally convey world knowledge. They are very costly to collect and not a lot of such datasets exist at this point (Wiegreffe and Marasović, 2021). Moreover, inferring high-quality explanations from very large language models necessitates excessive amounts of compute and storage. Thus, reproducing these results is out of scope.
cause model and human rationales rarely align perfectly, and thus the user’s trust may be unwarranted (Jacovi et al., 2021). Jacovi and Goldberg (2020) argue that faithfulness and plausibility are two ends of a continuous scale, and Atanasova et al. (2020) show that the correlation between these properties indeed is low.

This is why, in this work, we revisit the task of verbalizing saliency maps (Forrest et al., 2018; Mariotti et al., 2020) and formalize this task, i.e. translating the output of feature attribution methods into natural language. With this, we can balance the advantages and mitigate the pitfalls of former methods. Such verbalizations can describe complex relations between words and phrases and their associated saliency scores. At the same time, the comprehensiveness of an explanation can be adjusted more precisely using natural language, in comparison to heatmap visualizations.\(^3\)

We find that such a verbalization also comes with a few caveats: The natural process for human explainers is to select only the most relevant causes for an event. Humans have to make conscious decisions about what to say, since the cognitive load on the recipient’s end might become too big if the entire information is communicated (Hilton, 2017; Miller, 2019). Expressing saliency maps as NLEs could yield an unlimited amount of statements. The task of verbalizing the explanation requires selecting the most informative and useful aspects of it and communicating them concisely.

In this paper, we address the problem of saliency map verbalization (SMV) with the following contributions:

- We formalize the underexplored task of SMV and establish desiderata (§2);
- We employ efficient search methods and scoring metrics to select tokens and fill templates with them, constituting model-free SMVs (§3);
- We evaluate SMVs in two text classification setups and show that they are task- and model-invariant, informative and concise (§4).

2 Verbalizing saliency maps

2.1 Formalization

The setup of the saliency map verbalization task consists of an underlying (explained) model \( m \) whose prediction \( \hat{y} \in Y \) on source tokens \( W = w_1 \ldots w_n \) we want to explain (against the set of possible outcomes \( Y \)).\(^4\)

\( m \) is equipped with a feature explanation method (or short: explainer) \( e \) which produces a saliency
map \( S = s_1 \ldots s_n \):

\[
e(W, m) = S
\]

Here, we call token \( w_i \) salient towards outcome \( y^5 \) if its associated saliency score \( s_i > 0 \) and salient against \( y \) for \( s_i < 0 \). \( e \) can have many sources, e.g. gradient-based methods such as Integrated Gradients (Sundararajan et al., 2017) which we employ in our experiments (§4), or even human experts assigning relevance scores.\(^6\)

A verbalized saliency map \( S_V \) is produced by some verbalizer \( v \) that receives the output of \( e \):

\[
v(W, S) = S_V
\]

\( v \) can be any function that discretizes attribution scores and produces a natural language representation \( S_V \). This is connected to the concept of hard selection in DeYoung et al. (2020) and heuristics for discretizing rationales (Jain et al., 2020). We categorize verbalized saliency maps as an intermediate representation between feature attributions, extractive rationales (or highlights) and NLEs (Wiegreffe and Marasović, 2021). Moreover, verbalized explanations are procedural and deterministic by nature, i.e. they function as step-by-step rules or instructions that one can directly follow (Tan, 2022) to understand a model’s decision. In this regard, we also see similarities with compositional explanations (Hancock et al., 2018; Ye et al., 2020; Yao et al., 2021). Their primary use case is improving the performance of the underlying model with the help of crowd-sourced refinement advice.

### 2.2 Desiderata

In the following, we outline the interpretations of the two common evaluation paradigms for explanations, namely faithfulness and plausibility.

The plausibility of explanations can be measured with correlation with human ground-truth explanations (DeYoung et al., 2020; Jacovi and Goldberg, 2020), since gold rationales are influenced by human priors on what a model should do.\(^7\)

Regarding the concept of faithfulness, saliency maps express that “certain parts of the input are more important to the model reasoning than others” (linearity assumption in Jacovi and Goldberg (2020)). While sufficiency measures if the amount of information communicated through the explanation is enough to justify the prediction, comprehensiveness measures the difference in the model confidence with the salient tokens removed from the source (DeYoung et al., 2020).

Another type of faithfulness is the model assumption which requires two models to “make the same predictions [iff] they use the same reasoning process” (Jacovi and Goldberg, 2020). By extension this means a model has to be simulatable (Doshi-Velez and Kim, 2017), i.e. a human or another model should be able to predict a model’s behaviour on unseen examples while exposed only to the explanation and not the model’s prediction.

We will now introduce desiderata for SMVs.

Explainer-faithfulness Explainer \( e \) and verbalizer \( v \) are two separate processes, so the saliency map \( S \) can be seen as static. Therefore, the faithfulness of \( e \) to the model \( m \) is extrinsic to the verbalization. Instead, it is essential to faithfully translate \( S \) into natural language.

Conciseness A full translation into natural language is nonsensical, however, because all relations between the continuous-valued saliency scores and the associated tokens would not be useful for a human explainee. We want \( S_V \) to be concise, yet still contain the key information. Thus, we define a coverage metric to measure the loss of information from \( S \) to \( S_V \), i.e. how much of the total attribution in \( S = s_1 \ldots s_n \) is covered by the tokens mentioned in \( S_V = v_1 \ldots v_m \):

\[
\text{Coverage}(S_V) = \frac{\sum |v_i| \in S_V}{\sum S}
\]

Task- and model-invariance A verbalizer \( v \) should also be able to abstract away the downstream task and underlying model \( m \). Zooming in on one particular use case, task-specific information such as that adjectives are important for sentiment analysis should not be transferred to other tasks. If we gave the verbalizer \( v \) white-box access to the explained model \( m \) that may be fine-tuned on the specific task of sentiment analysis, the probability \( p \) of a verbalized explanation \( S_V \) should be

\(^{5}\)When evaluating explanations for simulatability, including \( y \) in the explanation would mean leaking the label. It depends on the use case of the explanation whether \( y \) can be included or not.

\(^{6}\)For an overview of commonly used methods, we refer the reader to Madsen et al. (2022).

\(^{7}\)It can also be evaluated in a functionally-grounded manner without relying on human judgments (Wiegreffe and Pinter, 2019).
Table 1: Illustration of the candidate generation and selection process with $k = 5$ and $q = .75$ with an instance from IMDb that is wrongly classified as positive sentiment. This instance received much higher ratings for helpfulness and ease of understanding (by 3.25 points on average) by annotators in our pilot study than its heatmap counterpart. All annotators also successfully simulated the model predicting positive sentiment. The final verbalization is a span that uncovers that the BERT model focuses on the “wrong” tokens. In our experiments, the label information in gray is not included in order to setup the simulation task correctly.

The span » way the story is good « is the most salient for the positive sentiment prediction.

the same regardless of it:

$$p(Sv|S) = p(Sv|m)$$

3 Method

We employ different binary filter algorithms as search methods (§3.1) and scoring metrics (§3.2) to select tokens for filling hand-crafted templates, constituting saliency map verbalizations. This approach does not require architectural changes to the underlying model or modifications to an existing saliency method. The most similar approach to our selection heuristics, to our knowledge, are the discretization strategies in Jain et al. (2020, §5.2).

In the following, we will present two distinct candidate generation methods that can both be combined with one of two scoring metrics. A final candidate selection (§3.3) will collect the results from both searches, concatenate them to possibly larger spans and filter the top scoring candidates once more while maximizing coverage (Eq. 3). These salient subsets are then used to complete hand-crafted templates (§3.4).

3.1 Explanation search

Convolution Search  Inspired by the convolutions of neural networks, we compare tokens that are located close to each other but are not necessarily direct neighbors. Coherence between pairs of tokens is solely determined by looking at their attributions with the following binary filters. In summary the following method firstly generates template-vectors that we then permute and keep as our binary filters. After computing all valid and sensible permutations, we can start calculating possibly salient or coherent snippets of our input. We choose $b \in \mathbb{N}$ vectors with a length of $c$. We describe these $b$ vectors $v_i$ as follows:

$$v_i = [0, 1, 1, 0, \ldots, 0, 1, c-i, 0, 1, c-i], \quad v_i \in \mathbb{Z}^{1,c}.$$  

We only keep those $v_i$ where $\sum v_i \notin \{0, 1, c\}$ in order to perform sensible permutations. For each $v_i$, we define a filter $f_{i,j}$, where each distinct entry in $f_i$ is a unique permutation of $v_i$. Let $A$ be our input, with $A \in \mathbb{R}^{1,k}, k > c$, then we multiply a subset of our input with every binary filter

$$r_{i,j,l} = f_{i,j} \cdot A_l^t + c,$$

$l \in L, L = \{k \in \mathbb{Z} | 1 \leq k \leq |A| - c\}.$

From this, we receive vectors containing possibly coherent attributions and tokens.

Span Search  Instead of looking for token pairs in a local neighborhood, we can also look for contiguous spans of tokens by adapting our proposed convolutional search. Let $c \in \mathbb{N}$, with $c$ being odd. We generate $b$ vectors of length of $c$. We describe these $b$ vectors as follows: Choose $i \in \mathbb{N}$. With $i$ being odd,

$$v_i = [0, 1, 1, 0, \ldots, 0, 1, i, 0, \ldots, 0], \quad v_i \in \mathbb{Z}^{1,c}.$$
Let $A$ be our input, with $A \in \mathbb{R}^{1,k}$, $k > c$, then we calculate attribution vectors $r_{i,t}$ as such:

$$r_{i,t} = v_i \cdot A_{l+c}^t,$$

$$l \in L, L = \{l \in \mathbb{Z} | 1 \leq l \leq |A| - c\} \quad (8)$$

### 3.2 Candidate scoring metrics

We score and filter the snippets so that we can present the most salient samples. As a threshold, we calculate the average of the $n\%$ most salient tokens of the given input sample. This simple method does not filter for saliency, but it reduces the likelihood of presenting non-salient sample snippets.

**Weighted average** The weighted average sums up all attribution scores of said snippet and divides it by the length of a candidate snippet. The resulting value is then compared to our baseline value $\beta$. If the score is greater, it gets considered salient and will be marked for verbalization.

**Quantile** The quantile method relies on the standard deviation within our sample. Given a quantile $n, n \in \mathbb{R}^+_0$, we calculate the corresponding standard deviation value $\sigma$ and compare it to the average of the values of our snippet. If the score is greater than $\sigma$ and our baseline value, it will be marked for verbalization.

### 3.3 Candidate selection

In addition to the two search methods in §3.1, we consider the $k$ single tokens with the highest attribution scores. After generating $k$ candidates from each search method, we concatenate neighboring token indices to (possibly) longer sequences and recalculate their coverage. We compute the $q$-th quantile of the remaining candidates according to their coverage values to select the final input(s) to our templates. If no candidate is within the $q$-th quantile, the highest scoring candidate span will be chosen. We find values for $q$ of $0.5 \leq q \leq 0.75$ to produce the right amount of candidates in the end, s.t. there almost always is at least one candidate in the $q$-th quantile and the resulting verbalization is not longer than most text inputs.

### 3.4 Templates for Verbalizing Explanations

We design our templates as atomic expressions with constraints and blanks that can be filled with words from $W$. In the most basic cases, we refer to spans, phrases, words and characters as salient or important for some prediction. Figure 1 and Table 1 show exemplary instances for our datasets (§4) and Appendix B provides further details.

Our template-based methodology satisfies the task- and model-invariance desideratum by design, because no task-specific model or NLG component is involved. Achieving sufficiency (measured by coverage) is harder, because a full translation of any saliency map is too verbose and thus not helpful.

### 4 Experiments

We choose datasets that cover a selection of English-language text classification tasks. In particular, we select IMDb (Maas et al., 2011) for sentiment analysis, and AG News (Zhang et al., 2015) for topic classification.

We retrieve predictions from BERT models on the test partitions of IMDb and AG News made available through TextAttack (Morris et al., 2020) and their Integrated Gradients (Sundararajan et al., 2017) explanations with 25 samples. All saliency maps were downloaded from the Thermostat library (Feldhus et al., 2021).

We then take subsets of each dataset according to multiple heuristics:

- Our search methods (Convolution, Span) both have non-zero results.
- Similar to human annotators only labeling the tokens supporting one outcome (Wiegrefe and Marasović, 2021), we restrict our experiments to explaining a single outcome – the predicted label $\hat{y}$ – and thus modify our metric (Eq. 3): $\text{Cov}_+$ only considers the positive attributions $s_i > 0$.
- We select instances achieving at least a $\text{Cov}_+$ score of 15% (indicating the attribution mass is not too evenly distributed, making interpretations of saliency maps challenging).
- We only consider instances with a maximum token length of 80, s.t. the human evaluation is more manageable for annotators.
- We select equal amounts of instances for every true label $y$ in each dataset.
- We pick 25% of instances to be wrong predictions of the underlying model, i.e. $y \neq \hat{y}$.

For each dataset, out of the remaining instances (1207/25000 for IMDb, 6130/7600 for AG News) we pick 80 IMDb plus 120 AG News instances for

\footnote{Although multiple models and explanation-generating methods are available, we specifically focus on one pair for both datasets, because the focus of our investigation is on the quality of the representation rather than the model.}

\footnote{The maximum token length heuristic excludes most in IMDb, but very few in the AG News.}
our evaluation at random. We apply the weighted average for IMDb-BERT-IG (β = 0.4) and the quantile scoring metric for AG News-BERT-IG (σ = 3). We choose the number of candidates to be k = 5 in all cases and the threshold q to be .75 for IMDb and .5 for AG News as the average length of the input is lower for the latter which results in too few candidates with higher qs.\footnote{We will make this dataset including our annotations available via our code repository.}

5 Evaluation

Automated evaluation methods like Area Over the Perturbation Curve (AOPC) (DeYoung et al., 2020) are not applicable for measuring the quality of our methodology, because we assume the saliency map-producing method ε and thus its faithfulness as given. Instead, we have to rely on a human evaluation and measure correlations with information loss, the abstraction factor and the complexity of saliency maps.

Inspired by previous crowd studies in explainability (Chandrasekaran et al., 2018; Strout et al., 2019; Hase and Bansal, 2020; Sen et al., 2020; González et al., 2021; Arora et al., 2022, i.a.), we evaluate the quality of our verbalizations in a small pilot study involving four annotators with computational linguistics background and proficiency in the English language (non-native speakers).

Each annotator was shown all 400 explanations consisting of equal amounts of verbalizations (SMV) and heatmap\footnote{We distinguish between saliency maps as an array of token-attribution pairs and heatmaps as visualizations usually including colors.} visualizations (HM) covering the same instances as the SMVs. In order to reduce cognitive affordances, we group explanation types in block sizes of 10 and do not randomize between the downstream tasks.

**Task A: Simulation** The annotators had to simulate the model, i.e. predict the model’s outcome only based on one type of explanation plus the input text (“What does the model predict?”).

**Task B: Rating** In a second task, we kept this setup, but instead asked to provide a rating on a seven-point Likert scale about (B1) “how helpful [they] found the explanation for guessing the model prediction” and (B2) “how easy [they] found the explanation to understand”. A higher rating indicates a higher quality of the explanation. Regarding the former, if the explanation does not provide any sensible clues about the predicted label, annotators still had to select a label in Task A and could express their dissatisfaction in B1. As a counterexample, in cases where y ≠ ỹ and the annotators expect y, but notice that the explanation hints at ỹ, we expect the rating in B1 to be high.

|      | Simul Acc | B1: Helpful | B2: Easy |
|------|-----------|-------------|----------|
| IMDb | All       | 88.75       | 4.94     | 4.36     | 4.68     |
|      | High [W]  | 85.9       | 4.87     | 4.17     | 4.63     |
|      | High Abs  | 84.87      | 4.92     | 4.26     | 4.76     |
|      | High Cov  | 93.75      | 5.22     | 5.15     | 4.48     | 5.0     |
|      | High q̃  | 83.78      | 4.93     | 4.34     | 4.81     |
|      | ỹ = y   | 63.75      | 3.71     | 3.4      | 3.56     |
| AG News | HM   | 71.67      | 5.64     | 5.13     | 5.13     |
|      | High [W] | 73.48      | 5.59     | 5.13     | 5.03     | 5.10     |
|      | High Abs | 75.93      | 5.61     | 5.25     | 5.03     | 5.25     |
|      | High Cov | 75.0       | 5.78     | 5.42     | 5.24     | 5.34     |
|      | High q̃  | 68.23      | 5.55     | 5.11     | 5.03     | 5.03     |
|      | ỹ = y   | 62.0       | 63.06    | 5.41     | 5.11     | 4.92     | 5.16     |

Table 2: Results of the human evaluation for all selected subsets. Simul Acc = Simulation accuracy (annotators guessing the label predicted by the underlying model correctly) in Task A. B1/B2 = Average rating of annotators (1 “bad” - 7 “good”) for helpfulness and ease of understanding. “High x” means we filter all instances that are below the mean value of x. HM = Heatmap visualization. SMV = Saliency map verbalization. Bold values indicate the representation with the highest value in a specific category.

6 Results

First, we measure a runtime of 7 minutes on a CPU to generate verbalizations for all 25k instances of IMDb. Given pre-computed saliency maps from any explainer, this is considerably faster than using an end-to-end model for extractive rationales, e.g. Treviso and Martins (2020), which takes several hours for training and then more than 10 minutes for inference on a RTX 3080 GPU.

Regarding our human evaluation, the comparison between SMVs and heatmaps (Tab. 2) shows that SMVs are generally easier to understand (B2). Annotators further reported that they also had to spend less time deciding on the model sim-
Figure 2: Correlations between automated metrics and human ratings in IMDb (l.) and AG News (r.). $|S_V|$ = Length of the verbalization. $|W|$ = Length of the input text. Abs = Abstraction factor from input text to SMV. Cov = Coverage score of SMV. $\delta$ = Complexity measured by sum of absolute differences between each value to its successor. $y = \hat{y}$ = Correct prediction by the model.

ulation task (A).\textsuperscript{12} Between the sets of 800 ratings from each annotator, we computed a Krippendorff’s $\alpha$ of 0.206.

In the following paragraphs, we will analyze six different subsets of the collected data.

**Downstream tasks** According to Jacovi et al. (2022), a feature attribution explanation aggregates all counterfactual contexts. This becomes apparent in our overall results on the AG News dataset where more than one potential alternative (multiclass classification with $|C| = 4$) outcome exists.

Annotators’ simulation accuracy drops from high 80s (IMDb) to around 70%.

**Length of the input text** We calculate the length of the input texts after cleaning up tokenization spaces. We do not record any substantial shifts in comparison to the overall scores, except for the ease of understanding rating (B2) being lower for heatmaps. This is expected, because annotators will spend more time on longer input texts.

**Length of the verbalization** The average lengths of the SMVs is about three times shorter than its corresponding input text (19 vs. 60) for IMDb and about half as long for AG News (23 vs. 39). We then evaluate how much more concise an SMV is compared to its input text by measuring the abstraction factor $\text{Abs} = \frac{|W|}{|S_V|}$. Table 2 illustrates that instances higher than average $\text{Abs} = \frac{3.25}{1.78}$ may result in better simulation accuracy and improved ratings over heatmaps.

\textsuperscript{12}We deliberately did not measure time, because distractions and other influences on the annotators would misrepresent the actual time needed to make a decision on a task that takes less than a minute per example.

**Coverage of the verbalization** The subset of instances with high coverage is substantially easier to simulate (IMDb) and elicits the highest ratings from annotators across all six measurements. These saliency maps usually only have a single or very few tokens that are very salient which makes them easy to read in both representations. Figure 2 points out moderate positive correlations with correct model predictions and annotator ratings.

**Complexity of the saliency map** To our knowledge, there is no standard measure for the complexity of saliency maps. We sum up the absolute differences between each value to its successor: $\delta = \Sigma |s_i - s_{i+1}|$. We do not explicitly incorporate sign change into this equation, but assume that large and frequent changes of saliency scores make saliency maps hard to decipher and discourage longer coherent spans of salient tokens. We notice an expected drop across all scores and hypothesize that the effect is small, because we already excluded most very difficult cases (§4). However, we also detect a moderate correlation with coverage in Figure 2. This reveals an imperfection with our $\delta$ metric, because single very salient tokens usually account for large increases in the overall sum. A more exact measure has yet to be devised.

**Wrong model predictions** Lastly, we investigate the subset of wrong model predictions ($y \neq \hat{y}$): The drop in simulation accuracy and ratings is more severe for IMDb through all types of explanations. In AG News, the simulatability and the ease of understanding turn out to be higher for SMVs.
6.1 Discussion

Reiterating Jacovi et al. (2022) and Schuff et al. (2022), we conclude that saliency maps are flawed as they don’t consider causality and mislead humans even in short instances from a binary text classification task (IMDb) and especially when the model failed to predict the correct label. We advocate looking beyond a one-for-all view on explanations by combining saliency maps with other types of sources: Counterfactuals can address the causality problem without the need to overwhelm the human with multiple saliency maps. Free-text rationales, although not as controlled in terms of faithfulness to the underlying model, can provide plausible explanations driven by world knowledge. Our SMVs lay the foundation for such hybrid explanations in a purely textual modality.

We acknowledge that SMVs have quite obvious drawbacks. First and foremost, the templates we employ make them repetitive and rigid and in some cases not inherently fit for human recipients, but the results show that they can guarantee a minimum degree of understandability (Ehsan et al., 2019) through fluency and grammatical correctness and optimizing for both sufficiency (via coverage) and conciseness (via $k$ and $q$ in §3.3) ensures the parsimony of explanations (Kulesza et al., 2015; Miller, 2019; Sokol and Flach, 2020). 13

7 Related Work

To our knowledge, the only previous saliency map verbalization approach is by Forrest et al. (2018) who used LIME explanations and a template-based NLG pipeline on a credit dataset. While they still include numerical values within an explanation, we focus on fully verbalized explanations in NLP tasks, because humans are more interested in reasoning than in numerical values (Reiter, 2019). Ampomah et al. (2022) created a dataset of tables summarizing the performance metrics of a text classifier and trained a neural module to automatically generate accompanying texts. We also found that the research questions in Kumar et al. (2021) can be seen as verbalized explanations, but they are not actual outputs of their framework. Tangentially related, the human-computer interaction (HCI) community highlighted the advantages of verbalization as a complementary medium to visual explanations (Sevastjanova et al., 2018; Hohman et al., 2019; Szymanski et al., 2021; Chromik, 2021).

Hsu and Tan (2021) introduced the task of decision-focused summarization. While there are overlaps in the selection of important subsets of the input, the textual nature of the output and the employment of saliency methods, our work is concerned with summarizing the token-level information provided by a saliency map from an arbitrary source for a single instance. Okeson et al. (2021) found in their study that global feature attributions obtained by ranking features by different summary statistics helped users to communicate what the model had learned and to identify next steps for debugging it. Rönnqvist et al. (2022) aggregated attribution scores from multiple documents to find top-ranked keywords for classes.

In early explainability literature, van Lent et al. (2004) already used template filling. Templates in NLE frameworks were engineered by Camburu et al. (2020) to find inconsistencies in generated explanations. While their templates were designed to mimic commonsense logic patterns present in the e-SNLI dataset (Camburu et al., 2018), our templates are a means to verbalize arbitrary token attributions. Paranjape et al. (2021) crafted templates and used a mask-infilling approach to produce contrastive explanations from pre-trained language models. Donadello and Dragoni (2021) utilized a template system to render explanation graph structures as text.

To our knowledge, there is not much research on how humans perceive and comprehend saliency maps in the NLP domain and what the particular differences between NLEs and saliency maps are. González et al. (2021) discovered that recipients of incomplete explanations may fill gaps with assumptions based on their own priors about what seems plausible. Schuff et al. (2022) found that people often misinterpret explanations such as saliency maps, because superficial, unrelated factors such as word length lead to a cognitive bias and influence their perception of the explanation. Our framework circumvents this pitfall, because verbalized explanations can reinforce the importance of specific tokens deemed salient by the source.

8 Conclusion

We find that saliency map verbalizations can act as human-centric extractive rationales without the need to train a dedicated model, and can compete with heatmap visualizations on human simulatability and helpfulness while achieving higher scores.
on ease of understandability. While our verbalizations can address misalignments between human and machine by reinforcing the importance of unexpectedly salient tokens and phrases, explicitly modelling expected highlights to mitigate misalignments as reported on in Schuff et al. (2022) and Prasad et al. (2021) is still an unexplored avenue of research. In the future, we hope to explore saliency maps in NLP in a broader crowdsourced study, since we could not investigate all factors and variables in this pilot study and there are still open questions regarding their affordances and relation to other work on extractive and free-text rationales.

Acknowledgments

We would like to thank Aleksandra Gabryszak, Akhyar Ahmed, Elif Kara, Ajay Madhavan Ravichandran, Tatjana Zeen, Arne Binder, Yuxuan Chen and David Harbecke for their valuable work and feedback. This work has been supported by the German Federal Ministry of Education and Research as part of the project XAINES (01IW20005).

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Acknowledgments

We would like to thank Aleksandra Gabryszak, Akhyar Ahmed, Elif Kara, Ajay Madhavan Ravichandran, Tatjana Zeen, Arne Binder, Yuxuan Chen and David Harbecke for their valuable work and feedback. This work has been supported by the German Federal Ministry of Education and Research as part of the project XAINES (01IW20005).

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A Limitations

Wiegreffe and Marasović (2021) pointed out that there are classes whose feature attributions do not inherently make sense. For example, the most important characteristic of “no hate speech” instances in the task of hate speech detection is the absence of such salient tokens. For these cases, our setup will not produce explanations that are easy to comprehend for humans.

Another complication which verbalized explanations introduce over numerical ones is the ambiguity problem when one token occurs more than once in the source.

We have not measured the amount of label leakage. Although our approach deals with hard constraints imposed through templates, there still might be instances in which certain selected spans leak the label. This is a problem with extractive rationales and heatmap visualizations as well that our verbalization methodology does not improve on. Future analyses should apply metrics such as LAS (Hase et al., 2020).

Lastly, there are still plenty of downstream tasks that explainability methods and especially saliency maps and extractive rationales have not yet been applied to, such as elaborate text generation tasks like summarization and story generation. While we claim that our approach is task- and model-agnostic, we have not shown this for these settings.
B List of templates

After detokenization,

- if the span is of length 1 and the token itself is of length 1, add “The character { token }”

- if the span is of length 1 and the token has a length above 1, add “The word { token }”

- if the span has a length above 1 and contains a sentence delimiting token such as a full stop, add “The span { span }”

- if none of the above applies, add “The phrase { span }”

The atomic verbalized explanation is then checked for its rank among the candidates according to the coverage metric.

- If the rank is 1, add “is most important for the prediction.”

- For any other rank, add “is also salient.”

We also hand-crafted templates for polarity and value comparison which we did not use in our human evaluation:

- If we want to express negative saliency which indicates tokens indicative for all counterfactual contexts: “{ token/span } is { not/least } salient.”

- If there are two candidates, we can insert a comparative (more/less) and write: “{ token₁ } is { comparative } salient than { token₂ }.”