

# The Struggles of Feature-Based Explanations: Shapley Values vs. Minimal Sufficient Subsets

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## Abstract

For neural models to garner widespread public trust and ensure fairness, we must have human-intelligible explanations for their predictions. Recently, an increasing number of works focus on explaining the predictions of neural models in terms of the relevance of the input features. In this work, we show that feature-based explanations pose problems even for explaining trivial models. We show that, in certain cases, there exist at least two ground-truth feature-based explanations, and that, sometimes, neither of them is enough to provide a complete view of the decision-making process of the model. Moreover, we show that two popular classes of explainers, Shapley explainers and minimal sufficient subsets explainers, target fundamentally different types of ground-truth explanations, despite the apparently implicit assumption that explainers should look for one specific feature-based explanation. These findings bring an additional dimension to consider in both developing and choosing explainers.

## 1 Introduction

A large number of explanatory methods have been developed with the goal of shedding light on black-box neural models (Ribeiro et al., 2016; Lundberg and Lee, 2017; Simonyan et al., 2014; Sundararajan et al., 2017; Carter et al., 2019; Camburu et al., 2018; Park et al., 2018; Kim et al., 2018). The majority of these methods explain the prediction of a model in terms of relevance of the input features (e.g., tokens for text). In this work, we show that explaining the predictions of even trivial models using only input features can be problematic. We show that there can be more than one ground-truth feature-based explanation and that two prevalent classes of explainers—Shapley explainers and minimal sufficient subsets (MSSs) explainers—target fundamentally different ground-truth explanations,

without explicitly mentioning it. On the contrary, current works seem to imply that there is only one ground-truth feature-based explanation for a prediction. We reveal strengths and limitations of each of the two types and show that, sometimes, neither of them can unambiguously reflect the decision-making process of a model. Our findings encourage deeper reflections on the types of explanations that one aims to provide, and give users an additional dimension to consider in order to pick an explainer.

## 2 Background

Among existing feature-based explainers, there are two major classes: (i) *feature-additive* and (ii) *minimal sufficient subsets*. To formally describe them, let  $m$  be a model to be explained and  $\mathbf{x}$  an instance with a potentially variable number  $n = |\mathbf{x}|$  of features:  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ . For example,  $x_i$  may be the  $i$ -th token in the input text  $\mathbf{x}$ .

### 2.1 Feature-additivity

A feature-additive explanation for the prediction  $m(\mathbf{x})$  consists of a set of importance weights  $\{w_i(m, \mathbf{x})\}_i$  associated with the features in  $\mathbf{x}$  such that their sum approximates the prediction<sup>1</sup> minus the bias of the model:  $\sum_{i=1}^{|\mathbf{x}|} w_i(m, \mathbf{x}) = m(\mathbf{x}) - m(\mathbf{b})$ , where  $\mathbf{b}$  is the baseline input, i.e., an input that brings no information, such as a zero-vector (Chen et al., 2018). The higher the absolute value of a weight, the more important the feature is for the prediction. The sign indicates whether the feature pulls towards the prediction (positive) or against it (negative). A large number of explanatory methods are feature-additive (Arras et al., 2017; Shrikumar et al., 2017; Ribeiro et al., 2016; Lundberg and Lee, 2017; Sundararajan et al., 2017).

<sup>1</sup>For classification, the probability of the predicted class.

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m: IF "very good" IN INPUT: RETURN 0.9;
    ELSE IF "nice" IN INPUT: RETURN 0.7;
    ELSE IF "good" IN INPUT: RETURN 0.6;
    ELSE RETURN 0.

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$\mathbf{x}^1$ : "The movie was good, it was actually nice." $m(\mathbf{x}^1) = 0.7$		$\mathbf{x}^2$ : "The movie was nice, in fact, it was very good." $m(\mathbf{x}^2) = 0.9$	
<u>Shapley explanation</u>	<u>MSS explanation</u>	<u>Shapley explanation</u>	<u>MSS explanation</u>
1. "nice": 0.4	{ "nice" }	1. "good": 0.417	{ "good", "very" }
2. "good": 0.3		2. "nice": 0.367	
		3. "very": 0.116	

Figure 1: Examples of cases with at least two ground-truth feature-based explanations. The Shapley values were computed via Eq. 1; the non-mentioned features received 0 weight.

**Shapley values.** Lundberg and Lee (2017) aim to unify all feature-additive explanatory methods by showing that the only set of importance weights that verify three properties (local accuracy, missingness, and consistency—we refer to their paper for details) is given by the Shapley values from coalitional game theory, i.e.,

$$w_i(m, \mathbf{x}) = \sum_{\mathbf{x}' \subseteq \mathbf{x} \setminus \{x_i\}} \frac{|\mathbf{x}'|!(|\mathbf{x}| - |\mathbf{x}'| - 1)!}{|\mathbf{x}|!} [m(\mathbf{x}' \cup \{x_i\}) - m(\mathbf{x}')], \quad (1)$$

where the sum enumerates over all subsets  $\mathbf{x}'$  of features in  $\mathbf{x}$  that do not include the feature for which the weight is computed. Lundberg and Lee (2017) provide methods (e.g., KernelSHAP) for approximating the Shapley values.

## 2.2 Minimal Sufficient Subsets

An MSS explanation of  $m(\mathbf{x})$  consists of a subset of features  $\text{mss}(m, \mathbf{x}) \subseteq \mathbf{x}$  such that the model gives (almost) the same prediction based only on the information from  $\text{mss}(m, \mathbf{x})$ , and no other subset of  $\text{mss}(m, \mathbf{x})$  leads  $m$  to the same prediction, i.e.,

$$m(\text{mss}(m, \mathbf{x})) = m(\mathbf{x}) \text{ and} \quad (2)$$

$$\forall \mathbf{s}' \subset \text{mss}(m, \mathbf{x}): m(\mathbf{s}') \neq m(\mathbf{x}). \quad (3)$$

To compute the prediction on a subset of features, one can eliminate the other features by occlusion (via a baseline feature) or deletion (if possible). MSSs explainers are increasingly popular (Chen et al., 2018; Yoon et al., 2019; Carter et al., 2019; Ribeiro et al., 2018).

## 3 Two Types of Ground-Truth Feature-Based Explanations

We show that, in certain cases, there exist more than one ground-truth feature-based explanation for a prediction, and that Shapley and MSSs explainers target two such different types of ground-truth explanations for even trivial models. We also

reveal strengths and limitations for each type, and we show that, sometimes, none of them is enough to provide a complete view on a model. To illustrate our findings, we give examples of hypothetical sentiment analysis models. Such models take as input a review and output a score reflecting the sentiment of the review towards the object of interest or towards an aspect of the object (for multi-aspect reviews) (McAuley et al., 2012). We treat the scores as real numbers linearly reflecting the intensity of the sentiment, with  $-1$  the most negative,  $1$  the most positive, hence,  $0$  being the neutral score. W.l.o.g., we assume that scores that differ by at least  $0.1$  indicate significantly different sentiments.

An example of a model  $m$  and two instances, each with two ground-truth feature-based explanations, is given in Fig. 1. The prediction of  $m$  on the instance  $\mathbf{x}^1$  is  $m(\mathbf{x}^1) = 0.7$ , as "nice" is present in the instance. Hence, one can argue that "nice" is the only important feature for this prediction. On the other hand, one may argue that "good" should also be flagged as important, because if "nice" is eliminated, then the model relies on "good" to provide a score as high as  $0.6$  instead of the much lower default of  $0$ . The difficulty faced when trying to explain  $m$  with feature-based explanations is even more pronounced on the instance  $\mathbf{x}^2$ . The model predicts  $m(\mathbf{x}^2) = 0.9$ , as "very good" is in  $\mathbf{x}^2$ . Hence, an explanation that states that the features "very" and "good" are the only important features for this prediction is one ground-truth explanation. However, if "good" is eliminated from this instance, the model relies on "nice" (and not on "very") to provide a score as high as  $0.7$ , while if both "good" and "nice" are eliminated, then the score drops all the way to  $0$ . From this perspective, "nice" can be seen as more important than "very", and an explanation that ranks "good", "nice", and "very" in this order of importance is also a ground-

1. ASPECT\_INDICATORS = {"taste", "smell", "appearance"} (AND ANY VARIATION, SUCH AS "Tastes")
2. SENTIMENT\_INDICATORS = {"amazing"  $\rightarrow$  1, "good"  $\rightarrow$  0.6, "refreshing"  $\rightarrow$  0.6, "bad"  $\rightarrow$  -0.6, "peculiar"  $\rightarrow$  -0.3, "horrible"  $\rightarrow$  -1}
3. A SENTIMENT INDICATOR IS ASSOCIATED TO ITS CLOSEST ASPECT (OCCLUDED TOKENS ARE COUNTED).
4. AN OCCLUDED TOKEN IS CONSIDERED TO BE NEUTRAL.
5. IF MORE SENTIMENT INDICATORS ARE ASSOCIATED TO AN ASPECT, THEN
  - (i) IF ALL ARE OF THE SAME SIGN: THE SCORE FOR THAT ASPECT IS THE SCORE OF THE STRONGEST SENTIMENT.
  - (ii) IF THERE ARE BOTH POSITIVE AND NEGATIVE SENTIMENTS ASSOCIATED TO THE ASPECT: THE SCORE FOR THAT ASPECT IS THE THRESHOLDED SUM OF SCORES ( $\text{MAX}(\text{MIN}(\text{SUM\_SCORES}, 1), -1)$ ).

$m^O$ : $s = \text{SUM OF SCORES OF ASPECTS}$ RETURN MAX(MIN( $s$ , 1), -1)	$m^S$ : RETURN SCORE OF SMELL	$m^T$ : RETURN SCORE OF TASTE
$\mathbf{x}^O$ : "The beer has an amazing appearance, a good smell, a bad taste."	$\mathbf{x}^{S1}$ : "Tastes horrible, peculiar smell."	$\mathbf{x}^{T1}$ : "Tastes good, refreshing."
$m^O(\mathbf{x}^O) = 1$	$m^S(\mathbf{x}^{S1}) = -0.3$	$m^T(\mathbf{x}^{T1}) = 0.6$
<u>Shapley explanation</u> 1. "amazing": 0.52 2. "good": 0.40 3. "bad": -0.23 4. "smell": 0.15 5. "appearance": 0.12 6. "taste": 0.03	<u>Shapley explanation</u> 1. "smell": -0.29 2. "Tastes": 0.26 3. "horrible": -0.14 4. "peculiar": -0.13	<u>Shapley explanation</u> 1. "Tastes": 0.4 2. "good": 0.1, "refreshing": 0.1
<u>MSS explanation</u> { "amazing", "appearance" }	<u>MSS explanation</u> { "peculiar", "smell" }	<u>MSSs explanations</u> { "Tastes", "good" }, { "Tastes", "refreshing" }
	$\mathbf{x}^{S2}$ : "Tastes amazing, peculiar smell."	$\mathbf{x}^{T2}$ : "Tastes amazing. The smell is also amazing."
	$m^S(\mathbf{x}^{S2}) = -0.3$	$m^T(\mathbf{x}^{T2}) = 0.6$
	<u>Shapley explanation</u> 1. "peculiar": -0.27 2. "smell": -0.10 3. "amazing": 0.05 4. "Tastes": 0.02	<u>Shapley explanation</u> 1. "Tastes": 0.58 2. "amazing <sup>1</sup> ": 0.42 3. "amazing <sup>2</sup> ": 0.08 4. "smell": -0.08
	<u>MSS explanation</u> { "peculiar", "smell" }	<u>MSSs explanations</u> { "Tastes", "amazing <sup>1</sup> " }, { "Tastes", "amazing <sup>2</sup> " }

Figure 2: Examples illustrating the strengths and limitations of the two types of feature-based explanations, as presented in Section 3.1. The five rules are common to all three models. The Shapley values were computed via Eq. 1, and written in decreasing order of their importance (absolute value); the non-mentioned features received 0 weight. In the last example, the superscript of "amazing" differentiates between its two occurrences.

truth explanation. Therefore, there are two fundamentally different perspectives on what a ground-truth feature-based explanation should be, even for this trivial model.

**Shapley vs. MSSs.** The above two types of ground-truth explanations are separately advocated by Shapley and MSSs explainers, as shown in Fig. 1. In particular, notice how the Shapley explanation attributes to "very" about three times less importance than to "nice" for  $m(\mathbf{x}^2)$ , while "nice" does not even make it in the MSS explanation.

This difference stems from the fact that Shapley values were introduced to promote *fairness* in distributing a total gain among the players of a coalition (Shapley, 1951). Hence, they provide the *average* importance of the features on a *neighborhood* of the instance, taking into account each player's performance in any sub-coalition. On the other hand, MSSs explanations provide the features that are *pointwise* important for the prediction on the instance *in isolation*, rewarding only the players that are crucial inside the *full* coalition.

**Not always distinct.** Although the two types of explanations are distinct for certain cases, in other cases they coincide. For example, for the model  $m$

in Fig. 1 and instances that contain exactly one of the subphrases "very good", "nice", and "good", such as "The movie was good.", both types of explanations point towards the same features.

**Literature.** To our knowledge, the existence of two types of ground-truth feature-based explanations was only briefly alluded by Sundararajan et al. (2017) when explaining the function  $\min(x_1, x_2)$  on the instance  $x_1 = 1, x_2 = 3$ . Their method attributes the whole importance weight (of  $1 = \min(1, 3) - \min(0, 0)$ ) to the *critical* feature  $x_1$ , while Shapley attributes 0.5 importance weight to each feature. They mention that preferring one explanation over the other is subjective.

On the other hand, Lundberg and Lee (2017) state<sup>2</sup> that all participants in their user study explained the function  $\max(x_1, x_2, x_3)$ <sup>3</sup> on the input  $x_1 = 5, x_2 = 4, x_3 = 0$  by attributing the importance weights of 3 for  $x_1$ , 2 for  $x_2$ , and 0 for  $x_3$ , implying that the Shapley explanation is the only ground-truth explanation for this function. However, the authors do not mention the number of

<sup>2</sup>Via a graph of results (their Fig. 4).

<sup>3</sup>Devised as a story of three people making money based on the maximum score that any of them achieved.

participants nor the guidelines that they received.

Moreover, current works, such as (Chen et al., 2018) and (Yoon et al., 2019), compare MSSs explainers (e.g., L2X and INVASE) with Shapley explainers on identifying the features used by a model trained on synthetic datasets, where the ground-truth important features are known. While the particular synthetic datasets used in these works do not violate either of the two ground-truth explanations, this is not mentioned at the time of comparison. Such comparisons risk to induce the idea that there is always only one feature-based explanation.

### 3.1 Strengths and Limitations

In this section, we reveal strengths and limitations of the two approaches presented above.

**Redundant features.** By looking only at the Shapley explanation for  $m(\mathbf{x}^1)$  in Fig. 1, one cannot know whether (1) the model requires *both* features “nice” and “good” to make its prediction of 0.7 (which is not the case for  $m$ ), or (2) one of these features is redundant in the presence of the other (which is the case for  $m$ ). In contrast, MSSs explanations do not contain redundant features (Eq. 3), and hence, the MSS explanation for  $m(\mathbf{x}^1)$  is able to distinguish between the two scenarios.

**Feature cancellations: genuine vs. artefacts.** In certain cases, there exist features that cancel each other out. Consider the model  $m^O$  in Fig. 2, which infers the overall sentiment on a beer from a multi-aspect review by adding up the scores that it associates to each aspect in the review. On the instance  $\mathbf{x}^O$ ,  $m^O$  predicts 1 by taking into account all three aspects. However, the MSS explanation is {“amazing”, “appearance”—it does not contain the features “bad”, “taste”, “good”, and “smell”, due to Eq. 3. Arguably, users may want to see the features from such a *genuine cancellation* in the explanation. Note that these features are flagged as important by the Shapley explanation, which, nonetheless, does not clearly indicate the perfect cancellation between “good smell” and “bad taste”. Moreover, the Shapley explanation gives the impression that “smell” and “appearance” are much more important (0.15 and 0.12) than “taste” (0.03), when, by design,  $m^O$  equally takes into account all aspects. Hence, neither the Shapley nor the MSS explanation is well reflecting the decision-making process for  $m^O(\mathbf{x}^O)$ .

Artefacts may occur when eliminating features from an instance, distorting the importance of certain features. Model  $m^S$  in Fig. 2 illustrates such an example. When  $m^S$  is applied to  $\mathbf{x}^{S1}$ , it predicts  $-0.3$ , and the MSS explanation is {“peculiar”, “smell”}, which, arguably, best reflects the decision-making process for  $m^S(\mathbf{x}^{S1})$ . However, in the Shapley explanation, “Tastes” appears to be twice more important than “peculiar”, and “horrible” appears as important as “peculiar”, even though “peculiar” is the actual sentiment indicator for smell. Furthermore, note how the Shapley importance weights dramatically change when only the sentiment on taste is changed in instance  $\mathbf{x}^{S2}$ , even though  $m^S$  does not rely on the sentiment on taste to predict the sentiment on smell.

**Multiple MSSs: genuine vs. artefacts.** In certain cases, there can exist multiple MSSs explanations for one prediction. For example, for the model  $m^T$  and instance  $\mathbf{x}^{T1}$  in Fig. 2, either of the features “good” and “refreshing” leads to the score of 0.6. Ideally, MSSs explainers provide all the genuine MSSs, e.g., both {“Tastes”, “good”} and {“Tastes”, “refreshing”}. However, many MSSs explainers are designed to retrieve only one MSS (Chen et al., 2018; Yoon et al., 2019). An exception is the SIS explainer (Carter et al., 2019), which retrieves a set of disjoint MSSs, which might also not be exhaustive (e.g., SIS would not retrieve the second MSS explanation for  $m^T(\mathbf{x}^{T1})$ , because “Tastes” is already taken by the first MSS). On the other hand, the Shapley explanation gives the same importance to both “good” and “refreshing”. However, with this explanation alone, one would not be able to know whether both “good” and “refreshing” are necessary to be present or if each individually suffices for the prediction of 0.6.

Artefacts occurring when eliminating features can also lead certain subsets of features to appear as MSSs. For example, for  $m^T$  and  $\mathbf{x}^{T2}$  in Fig. 2, either of the two occurrences of “amazing” forms an MSS, but the second one is not reflecting the decision-making process of the model. The Shapley explanation makes the distinction in this case.

**Discussion.** Our findings suggest that the use of both the MSS and the Shapley explanation together could lead to a better understanding of the decision-making process of a model for a prediction. For example, on the instance  $\mathbf{x}^1$  in Fig. 1, if one has both the Shapley and the MSS explanation, one would conclude that “nice” is enough for



the prediction of the model on that instance, and that “good” is redundant in the presence of “nice” but still an informative feature for this model. Similarly, for the instance  $\mathbf{x}^O$  in Fig. 2, having both explanations allows one to conclude that the model cancels out “good smell” and “bad taste”, which would not have been possible to infer from any of the two explanations alone. Hence, by categorizing the differences between the two types of explainers, our work shows their complementarity, provides as quick action the usage of both types of explanations, and opens the path towards more combinations of features, such as counterfactual or examples-based explanations.

We use simple rule-based models to expose the problematic characteristics of the explainers, first because one does not know how a complex neural network makes its decisions, which is the reason in the first place to develop explainers. Hence, we assess the explainers on rule-based models whose inner workings we know. Second, if explainers exhibit certain problems even on simple models, very likely, these problems would only increase with the complexity of the model to be explained. Third, the rule-based models that we exemplify are not at all unrealistic: neural networks were shown to learn to rely on combinations of input features to provide their predictions in different tasks, for natural language processing and beyond (see, e.g., (Gururangan et al., 2018; Ribeiro et al., 2018)). Hence, we expect that the problems that we raised with the simple rule-based examples would only get worse when the explainers are applied to real-world neural models.

## 4 Summary and Outlook

In this work, we showed that, for certain cases, there is more than one ground-truth feature-based explanation for the prediction of a model, and that Shapley explainers and MSSs explainers aim to provide two such fundamentally different ground-truth explanations. We also provided insights into the strengths and limitations of these types of explanations. Future work includes user studies to decide to what extent users benefit from each of these types of explanations or from their combination. Most importantly, this work encourages future reflections on the types of explanations that we provide.

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