How (Not) To Evaluate Explanation Quality

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Abstract

The importance of explainability is increasingly acknowledged in natural language processing. However, it is still unclear how the quality of explanations can be assessed effectively. The predominant approach is to compare proxy scores (such as BLEU or explanation F1) evaluated against gold explanations in the dataset. The assumption is that an increase of the proxy score implies a higher utility of explanations to users. In this paper, we question this assumption. In particular, we (i) formulate desired characteristics of explanation quality that apply across tasks and domains, (ii) point out how current evaluation practices violate those characteristics, and (iii) propose actionable guidelines to overcome obstacles that limit today’s evaluation of explanation quality and to enable the development of explainable systems that provide tangible benefits for human users. We substantiate our theoretical claims (i.e., the lack of validity and temporal decline of currently-used proxy scores) with empirical evidence from a crowdsourcing case study in which we investigate the explanation quality of state-of-the-art explainable question answering systems.

1 Introduction

While deep neural network models, such as transformers, achieve state-of-the-art results on many natural language processing (NLP) tasks, they are largely black-box models. This raises the need to provide explanations along with system predictions. Explanations are especially important when deploying models in real-world scenarios with human end-users (Angwin et al., 2016; Rudin et al., 2018). Explanations can be given in the form of model interpretations (such as heatmaps showing, e.g., integrated gradients (Sundararajan et al., 2017) or attention weights (Wiegrefe and Pinter, 2019)) or additional model predictions (such as supporting facts (Yang et al., 2018) or generated textual explanations (Camburu et al., 2018)).

One limiting factor in developing interpretable or explainable models the lack of adequate evaluation. A proper evaluation is key to compare different models and drive our research directions. Therefore, we focus on the evaluation of explanation quality in this paper. We show that the current state of explanation quality evaluation is insufficient and needs to be addressed explicitly to ensure the usefulness of explanations in real-world settings.\textsuperscript{1}

Currently, explanations are typically evaluated against gold explanations using proxy scores, such as BLEU or F1 (Camburu et al., 2018; Yang et al., \textsuperscript{1}Work done prior to joining Amazon.

\textsuperscript{1}Note that our discussion is independent of the different types of explanations mentioned before (heatmaps, extracted text, etc.) as well as of the model’s task.

\textsuperscript{†}Work done prior to joining Amazon.
but there is already work questioning the correlation of those scores with human perception, such as Schuff et al. (2020); Narang et al. (2020); Schuff et al. (2021). In Figure 1, we illustrate correlation coefficients between human ratings and automatic proxy scores for the explainable question answering task that we investigate in our case study in this paper. It can be seen that none of the proxy scores is sufficiently correlated with the human scores (axes are cropped at 0.8 for better readability). All of them are especially lacking correlation with, e.g., mental effort and perceived explanation utility. Moreover, the different scores cannot be mapped to isolated aspects of explanation quality.

Based on those observations, we ask how can we ensure a proper evaluation of explanation quality? In order to answer this question, we first need to define what explanation quality actually is, i.e., which general characteristics does explanation quality have? We discuss this question in Section 2, on the basis of findings from social sciences, such as Miller (2019). After formulating general characteristics of explanation quality, we investigate whether current evaluation practices adhere to these characteristics in Section 4 and address the question what are the shortcomings of current evaluation practices? Finally, we develop guidelines in Section 5 to overcome those obstacles on the way to effective explanation quality evaluation and discuss their advantages and limitations. We propose Pareto Front Leaderboards as one concrete approach to combine multiple evaluation scores and tackle the shortcomings of single-score leaderboards.

In addition to our theoretical argumentation that we base on examples and existing theories, we also substantiate our claims with empirical evidence from a crowdsourcing study investigating explainable question answering systems from the HotpotQA (Yang et al., 2018) leaderboard. In order to ease the understanding of our paper, we already introduce the case study in Section 3 and then describe its results within Section 4 and 5. Our analysis supports the hypothesized lack of proxy score validity, the corresponding conflation of quality dimensions and the erosion of target scores over time (i.e., Goodhart’s Law.) In the last part of the case study, we illustrate how our proposed leaderboard alternative can be applied in practice using the HotpotQA systems as an example.

2 Characteristics of Explanation Quality

Criteria for high-quality explanations have mainly been discussed in social sciences so far. Besides the definition of features for good explanations, such as coherence (Thagard, 1989; Ranney and Thagard, 1988; Read and Marcus-Newhall, 1993), soundness or completeness (Kulesza et al., 2013), literature has pointed out the importance of the explainees (Miller, 2019) and their goals (Vasilyeva et al., 2015).

Based on this prior work, we discuss characteristics of explanation quality in NLP in this section. Note that we assume the faithfulness of an explanation and only focus on characteristics for its perceivable quality.\(^3\)

2.1 User-Centered Explanation Quality

We argue that in AI, an explanation exists only in relation to a system that should be explained (the explanandum) and the human that receives the explanation (the explainee). We base this definition on the social process function of an explanation described by Miller (2019).

Given that explanations are always targeted towards a specific group of users, we argue that explanation quality needs to be assessed in the same or at least a similar context. In the following paragraphs, we give examples why this is important for explanations and the evaluation of their quality.

Goals of Target Users. The quality of an explanation depends on the goals of the target users (Vasilyeva et al., 2015). Consider an explanation in the form of a heatmap. It might be sufficient for an NLP developer or researcher who aims at analyzing and improving the system. However, it might not fit the needs of an end-user who has no machine-learning background but uses the system in practice. In the latter case, the quality of the explanation should be considered lower than in the former case because, e.g., the mental effort to process the explanation will be higher.

Background of Target Users. Taking end-users as an example, the background knowledge of users determines which type and extent of explanations are most useful for them (Suresh et al., 2021; Preece et al., 2018; Yu and Shi, 2018). For example, a perfect explanation in Spanish is useless if the end-user has no knowledge of the language.

\(^3\)We consider explanation characteristics that can be judged without access to, e.g., the underlying model. Regarding the evaluation of faithfulness we refer to the discussion of Jacovi and Goldberg (2020).
to a monolingual English speaker. Similarly, an “explanation” as it is provided by means of the coefficients of a linear model is useless to a user with dyscalculia.

**Perception of Target Users.** Even if an explanation perfectly explains the model prediction and meets certain quality criteria, the perception of the explanation by the user might be biased. Schuff et al. (2022) showed that the perception of heatmaps can be biased by different factors like word length.

**Intersubjectivity.** Those examples show that explanation quality is directly connected to the explainees. Different explainees will perceive the same explanations differently. Nevertheless, a group of “similar” explainees (e.g., Spanish native speakers reading a generated Spanish text) may share their opinion about the explanation. Therefore, we argue that explanation quality is *intersubjective*. This observation has two immediate implications: (i) every evaluation of explanation quality is limited to a specific group of explainees and (ii) explanation quality can be objectively evaluated only within a specific group of explainees.

### 2.2 Orthogonal Dimensions of Explanation Quality

Till date, systems are typically ranked focusing on a single score (see Section 4.3). We argue that there are different dimensions of explanation quality that are orthogonal to each other and should, therefore, be measured by several scores, such as plausibility (Zini et al., 2022), faithfulness (DeYoung et al., 2020) or model simulatability (Hase and Bansal, 2020). Consider the following thought experiment: Given an explanation that explains the decision process of a system A in a way that (a) faithfully reflects the system decision process and (b) plausibly convinces a user of the correctness of the prediction given the task input. We then replace the system with a new system B while keeping the explanation constant. The explanation will still be plausible to the user, however, if system B has a different decision process, the explanation cannot be considered to be faithful anymore as it is not clear whether it actually explains the model’s inner workings. Consequently, the two explanation quality dimensions faithfulness and plausibility are independent and it is not possible to holistically measure them with the same score.

### 3 Case Study: HotpotQA

In order to substantiate our following discussion with empirical evidence, we conduct a crowdsourcing study analyzing systems from the HotpotQA leaderboard. HotpotQA is an explainable question answering task proposed by (Yang et al., 2018). Details about the task, the dataset and the evaluation scores can be found in the appendix. Our case study consists of two parts: (i) An analysis of current evaluation practices (see Section 4.4 for results) and (ii) an evaluation of our proposed guidelines (see Section 5.4 for results).

#### 3.1 Case Study Design

To obtain a clear perspective onto (i) the relation between proxy scores and human ratings and (ii) the model ranks regarding various human ratings, we analyze test set predictions of 10 real model submissions as well as five synthetic models which we generate from different combinations of the gold annotations and randomly sampled answers and supporting facts (see appendix for more details). We evaluate the models in a crowdsourced user study in a between-subjects experiment with 75 participants from the US, collecting subjective quality ratings of *utility, consistency, usability, correctness* and *mental effort* as well as objective completion time measures.

For each model, we collect ratings from five crowdworkers who each rate a sample of 25 questions drawn from a pool of 100 questions. We provide details on the models, study design and questions that we asked the participants in the appendix.

Note that although Schuff et al. (2020) already conduct a human evaluation to investigate the relation between the different proxy scores and various human ratings/signals for the HotpotQA task, their evaluation is limited to three models and the ground truth predictions and is conducted on the public validation set only.

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4 In our case study, we focus on the distractor setting leaderboard available at https://hotpotqa.github.io/.
5 We thank the HotpotQA maintainers for providing us with the predictions and the system submitters for giving us their consent to include their model in our case study.
6 In order to support our assumption that a pool of 100 questions is sufficiently representative, we simulate experiments with various question subsets. We find that correlations already stabilize for as few as 20 questions and that there are no qualitative or quantitative differences to using 100 (all $\tau$ differences<=0.04 as shown in Figure 8 in the appendix).
Figure 2: Overview of the main shortcomings in current evaluation practices: (i) Disconnected of proxy scores and user perception (unvalidated proxy scores, neglection of users), (ii) conflation of multiple dimensions into proxy scores, and (iii) single-score leaderboards.

4 Shortcomings of Current Evaluation Practices

Explanation evaluation in NLP is mainly performed automatically (Yang et al., 2018; Camburu et al., 2018; DeYoung et al., 2020; Atanasova et al., 2020), borrowing proxy scores from other tasks, such as accuracy, F1, BLEU (Papineni et al., 2002) or BLEURT (Sellam et al., 2020). DeYoung et al. (2020), for example, propose to use automatic measures to evaluate explanation quality aspects, such as faithfulness, comprehensiveness and sufficiency. While they compute a variety of automatic scores that capture (a) how faithful a model’s predictions are (which they operationalize using comprehensiveness and sufficiency measures) and (b) how similar a model’s predictions are to human-annotated rationales, their evaluation does not include a human evaluation of the model explanations and leaves open how their proposed measures relate to user-perceived explanation characteristics. Other works evaluate explanation quality more indirectly, such as Pruthi et al. (2022) who evaluate saliency explanations via the accuracy gains they provide when training a student model on a teacher model’s explanations.

In the following, we present common evaluation practices and assess to which extent they conflict with the explanation quality characteristics presented in Section 2. Figure 2 provides an overview of the main challenges.

4.1 Unvalidated Proxy Scores

The underlying assumption of using proxy scores for evaluating explanation quality is that an improvement in proxy scores implies an increase in user benefits. However, to the best of our knowledge, there is no established view to which extent those scores actually reflect the value of explanations to users (i.e., to which extent it is valid and measures what it should measure). This practice conflicts with both the user-centered (Section 2.1) and the multidimensionality characteristic (Section 2.2) of explanation quality.

Validity is Explainee-Dependent. Similar to explanation quality, we argue that the validity of scores is target-user-dependent. Imagine a score that measures explanation completeness. It might adequately reflect user utility for an explainee group of analysts that spend much time reviewing a system’s explanation. However, it might be unrelated or even inversely related to user utility for an explainee group in a real-time environment that does not allow to review long explanations in detail.

Validity Might Change. Even if we had a score (proxy score or human rating score) that is valid, i.e., it measures one dimension of explanation quality in a decent way, using this score as the sole ranking criterion of a leaderboard can subvert its validity over time. This effect is explained in Goodhart’s Law that is commonly stated as “when a measure becomes a target, it ceases to be a good measure” (Goodhart, 1975; Campbell, 1979; Strathern, 1997; Manheim, 2018; Manheim and Garrabrant, 2018). Thomas and Uminsky (2022) discuss this in the context of AI and highlight the field’s problematic reliance on (single) metrics including the issue of metrics being gamed (Bevan and Hood, 2006). Let’s imagine that an initial investigation of some systems showed that explanation F1 is highly correlated with usability. Thus, it can be considered a valid proxy score. If now more and more systems are developed with the goal of reaching higher F1 scores, the set of models from our initial investigation does no longer represent the new model population. As a result, it cannot be ensured that the original correlation still holds.

Conflating Different Dimensions. Since proxy scores typically conflate different dimensions of explanation quality (see Figure 1), information about the individual independent dimensions is lost and cannot be recovered. For example, given two systems with similar proxy scores, it cannot be determined which one was superior in terms of individual explanation quality aspects, such consistency or understandability. Consequently, it is not possible
Figure 3: Kendall’s $\tau$ correlation coefficients for the correlation of different automatic scores and user-rated quality dimensions illustrating the weak and conflated connection and between proxy scores and human assessment (from left to right: scores evaluating answer correctness, scores evaluating correctness of supporting facts, scores jointly evaluating answer and fact correctness, additional scores like LocA and surface scores). Axes cropped at 0.6.

to identify an isolated improvement of a model in some of those aspects in the proxy score. For example, when we improve the proxy score, we cannot assess whether we actually improved all quality aspects or only a subset of them (and possibly decreased the performance on others). Similarly, a targeted improvement of particular quality aspects (e.g., for a particular use-case) is not possible.

4.2 Neglecting Users

Most studies only evaluate systems on proxy scores, neglecting human evaluation or large-scale qualitative analysis. This can be problematic even if we had valid proxy scores (Thomas and Uminsky, 2022). Note that current evaluation practice with automatic scores is questioned in many contexts in NLP today, especially in NLG (Callison-Burch et al., 2006; Liu et al., 2016; Novikova et al., 2017; Sulem et al., 2018; Reiter, 2018). We argue that alternative forms of evaluations, in particular human evaluation, are required to account for the characteristics defined in Section 2. To account for user-centered evaluations (Section 2.1), user studies ideally should be performed in similar contexts as the system will be applied in later. For multidimensionality (Section 2.2), user studies can comprise (i) a broader set of quantifiable dimensions than proxy scores as well as (ii) dimensions of explanation quality that are inaccessible using quantitative methods but require qualitative approaches, such as mental model analysis (Schrills and Franke, 2020; Kulesza et al., 2013) or thematic analysis (Braun and Clarke, 2006) in which themes are extracted from textual responses or transcriptions via various steps (coding, theme generation and review etc.). We illustrate these shortcomings using the streetlight effect phenomenon: Searching for valuable systems based on proxy metrics alone resembles the Streetlight Effect also known as the Drunkard’s Search Principle (Kaplan, 1964; Iyengar, 1993). This effect describes a situation in which a drunken man lost his keys in a park, but instead of searching for them in the place where he lost them, he is searching under a streetlight because this is where the light is. We argue that we face a similar situation when we exclusively rely on proxy metrics. Instead of focusing on what we ultimately are interested in, i.e., providing good explanations to users, we narrow our focus onto increasing proxy metrics instead. To shed light on the users of our system, our quantitative measures should include both validated proxy scores and human ratings/signals.

4.3 Single-score Leaderboards

The current practice in NLP leaderboards (and many NLP research work in general) is the scoring and comparing of systems using a single score. In Section 2.2, we already motivated that explanation quality has multiple independent dimensions. Therefore, it should be measured with multiple scores. Moreover, aggregating those scores (e.g., via averaging) to obtain a single measure will not be expedient either since the dimensions might be independently useful and scaled differently.

Ranking systems using a single score will also lead to over-optimization of this one score (Thomas and Uminsky, 2022). This could be prevented by using a diverse set of scores instead since the over-optimization of one score will likely lead to a deterioration of other scores.

4.4 Case Study Part I: Analysis of Current Evaluation Practice

In the first part of our case study, we analyze current evaluation practices for the HotpotQA leaderboard to see to which extent we can find the shortcomings described earlier in this section.

The leaderboard includes a variety of proxy
scores, such as exact match, precision, recall and F1 for the three aspects: answer, supporting facts and a combination of both. In our analysis, we also include the LocA score that measures to which extent predictions and explanations are coupled (Schuff et al., 2020). Furthermore, we include additional surface scores like the number of predicted supporting facts and the resulting number of words. We find that the leaderboard follows the same practices as we described in Section 4. Figure 3 shows Kendall’s τ correlation coefficients between (a) the automatic scores included in the leaderboard and (b) the human ratings we collected in our study. This more detailed version of Figure 1 confirms that the used proxy scores confute different dimensions of explanation quality and none of the scores is highly correlated with explanation quality dimensions like perceived explanation utility (Section 4.1).

Furthermore, the leaderboard does not include human ratings or signals in its evaluation (Section 4.2) and ranks the systems using a single score: joint F1 (Section 4.3). Figure 4 shows the Kendall’s τ correlation coefficients between joint-F1 and human ratings for various 12-month moving windows over the HotpotQA system submissions. The decrease from moderate positive correlations to lower and even negative correlation values for all human ratings except usability supports our hypothesis that Goodhart’s law affects today’s leaderboards.

5 Guidelines

In this section, we propose guidelines to address the shortcomings described in Section 4.

5.1 Validate Proxy Scores Against Humans

While there is a lot of work on investigating the relation between automatic scores and human ratings in natural language generation (Belz and Reiter, 2006; Novikova et al., 2017; Dušek et al., 2019), only few studies consider this aspect in the context of explanation evaluation (Jannach and Bauer, 2020; Schuff et al., 2020, 2021). To address the problem of unvalidated proxy scores for explanation quality evaluation (Section 4.1), we advise to validate the correlation between proxy scores and human signals, such as human ratings, completion times or physiological measures like eye tracking.

Advantages. Given proxy scores with a sufficient correlation with human signals of interest, those scores can be used for the development of systems that are actually useful for target users.

Limitations. Given a new task or leaderboard, it is unlikely that we have access to a representable pool of models which can be used to validate the metrics. Therefore, we have to accept a certain grace period in which we can only assume that the chosen evaluation scores lead to reasonable results. Once there is a handful of models available, the proxy metrics should then be validated against human benefit and revised if necessary.

Referring to our discussion of Goodhart’s law in Section 4.3, any proxy metrics (or human rating) has to be periodically re-tested for its validity.9

Finally, each validity evaluation is limited to a group of explainees (see Section 2.1). Different groups of users will have different needs and, as a result, explanation quality evaluation will need different measures. For example, validity findings for the population of high-school students might not transfer to the population of adult NLP researchers.

9The need for re-testing can be recognized by, e.g., monitoring demographic changes in the target population and/or changes in the correlations within user ratings, which can signal concept drift and potential loss of validity.
5.2 Do Human Evaluation Periodically

In Section 5.1, we already recommend user studies for the purpose of proxy score validation. Based on our discussion in Section 4.2, we also propose to do human evaluation in order to collect human rating scores as additional explanation quality indicators. In the context of application-oriented model development, human evaluation can be conducted after model tuning as the final evaluation. In the context of leaderboards, we propose to regularly conduct human assessments of (a subset) of system submissions. Following Jannach and Bauer (2020) and Thomas and Uminsky (2022), we advocate to also collect qualitative feedback (e.g., as comments within an evaluation or within a focus group) to complement quantitative measures.

There is already some related work on human evaluation of explainability that studies how different explanation methods affect specific aspects, such as simulatebility (Hase and Bansal, 2020), users’ response times, task accuracies (Lage et al., 2019a) or perceived system accuracy and explanation meaningfulness (Nourani et al., 2019a).

Advantages. Human evaluation allow us to re-adjust the direction into which we develop systems by unveiling explanation quality dimensions that were previously unknown. For example, qualitative findings from user comments can help us to identify system qualities we did not think of before.

Moreover, human evaluations could reward systems that follow an unconventional approach and, as a result, whose explanation qualities might be hidden in proxy scores. This could motivate researchers to develop original models and can ultimately diversify and accelerate research.

Limitations. Each human evaluation is bound to noise w.r.t. the pool of participants and the way they approach the study (for example whether they carefully read the questions). Further aspects that might hinder the conduction of a user study are potentially high costs to compensate the participants and longer preparation times to recruit participants and conduct and carefully evaluate the studies.

5.3 Use Various Scores for Evaluation and Pareto Front Leaderboards

As we argued in Section 4.3, using a single score for evaluation (regardless of proxy scores or human ratings/signals) can be misleading. Therefore, we propose to use various scores for evaluation rather than trying to weight different quality dimensions against each other to obtain a single score. This is in line with the recommendations by Thomas and Uminsky (2022). While prior work proposed leaderboards using on-demand (crowdsourcing) evaluation (Chaganty et al., 2017) and personalized utility rankings (Ethayarajh and Jurafsky, 2020), we are – to the best of our knowledge – the first to provide an actionable solution that does not condense multiple scores into a single one.

To be able to compare systems based on multiple scores, e.g., on a leaderboard, we propose to leverage the concept of Pareto efficiency. In the context of multidimensional leaderboards, a system is called Pareto efficient if the only way to select another system that is better regarding any score dimension is to worsen another score dimension. For example, system A is Pareto efficient if the only way to select another system to increase, e.g., the F1 score, is to choose a system that has a lower, e.g., accuracy. Given a set of systems, multiple systems can simultaneously be Pareto efficient. Figure 5 shows an example with nine systems (visualized by points) and two scores $q_1$ and $q_2$ of explanation quality (visualized by axes). In this plot, all five systems on the so-called Pareto front (“front 1”) are Pareto efficient, thus should have rank 1. In order to rank the remaining systems, we propose to remove those five systems from the set of systems and calculate the next Pareto front (“front 2”), and repeat this until all systems are ranked. The resulting leaderboard of the fictional systems shown in Figure 5 would consequently have five models on the first place (front 1), two models on the second (front 2) and two models on the third (front 3).

Advantages. Using multiple scores for evaluation offers the advantage of capturing diverse aspects of a system. If a sufficiently diverse set of scores is used, the over-optimization of one score can be prevented since other scores would likely be decreased at the same time. This can be motivated by the concept of surrogation. (Choi et al., 2012, 2013) In the context of manager compensation, Choi et al. (2012) find that manager decisions can be improved when “managers are compensated on...
multiple measures of a strategic construct” instead of on a single one. We hypothesize that this observation also holds for AI practitioners that need to choose a system, e.g., from a leaderboard.

When using Pareto front leaderboards, we can rank systems without weighting the different quality dimensions against each other. In particular, the concept of Pareto efficiency allows us to choose systems that are not worse than others on all fronts. Note that the Pareto front results hold regardless of a re-scaling of the dimensions and even are applicable to ordinal data, such as Likert ratings.

**Limitations.** With multiple scores, it can be hard to determine a “winning” system because different models might rank best on different scores. Pareto Front Leaderboards can mitigate this problem, however, they may result in a set of (instead of a single) winning systems. We argue that this is not a limitation though since the concept of Pareto efficiency ensures that a system on one front is not worse than other systems on the same front.

However, in the extreme case when the number of scores is high in comparison to the number of systems that should be scored, the resulting leaderboard can collapse to a single Pareto Front because the surface of the front grows exponentially with the number of scores. In this case, a ranking based on the Pareto Front will be meaningless. We therefore recommend to ensure that the number of variables should only be increased along with a sufficient increase in the number of systems.

Further, Pareto Front leaderboards can be “attacked” by only optimizing a single metric with the purpose of positioning a new system inside the first front. Although this allows the leaderboards to be gamed to a certain extent, a truly remarkable improvement is one that creates a new front which is robust to the improvement of single metrics.

5.4 Case Study Part II: Guideline Evaluation

**Qualitative Human Evaluation.** To illustrate one advantage of human evaluation (Section 5.2), we review participants’ voluntary free-text comments. Participants had two ways of providing comments: (i) on a question level and (ii) on an experiment level after completing all questions.

On the question level, participants told us that they considered the difficulty of the question when rating the performance of the system (“tricky question [...] impressive the correct answer was given”). Thus, in future evaluations, the difficulty level of the question (which is already annotated in HotpotQA) should be taken into account. Further findings are included in the appendix.

On the experiment level, users noted that answer correctness can sometimes not be determined binary (“a lot of things were ’probably’ or ’assumedly’ true [...] there could be multiple correct answers”). Furthermore, supporting facts alone might not be enough to satisfy a user’s needs w.r.t. explainability (“I never totally felt like I knew how the system worked”). This is in line with our user-centered definition of explanation quality (Section 2.1). Depending on the use case, different types of explanations might be better than others.

**Various Scores and Pareto Front Leaderboards.** We evaluate the 15 models described in Section 3.1 on numerous (i) human ratings and (ii) automatic scores. Then, we construct two Pareto front leaderboards, one for human ratings and one for automatic scores. Table 1 shows the leaderboard based on human ratings (usability, mental effort, utility, correctness, consistency and completion time). We observe that high-performing models, such as FE2H on ALBERT (leaderboard rank 1) are located within the rank 1 Pareto front en-par with the gold prediction system. Interestingly previously lower-ranked models, such as IRC (leaderboard

| Rank | Models |
|------|--------|
| 1    | gold (*), random-answers-gold-facts (*), FE2H on ALBERT (1), Longformer (23), S2G-large (29), HGN (33), Text-CAN (45), IRC (61) |
| 2    | AMGN (14), SAE (46), GRN (63), DecompRC (unranked), random-answers-random-facts (*), gold-answers-all-facts (*) |
| 3    | gold-answers-random-facts (*) |

Table 1: Ranked Pareto fronts based on human rating scores. The ranks of models on the actual HotpotQA leaderboard ranks are in parentheses.
Table 2: Ranked Pareto fronts based on automatic scores. The ranks of models on the actual HotpotQA leaderboard ranks are in parentheses.

| Rank | Models                                                                 |
|------|------------------------------------------------------------------------|
| 1    | gold (*)                                                              |
| 2    | gold-answers-all-facts (*), random-answers-gold-facts (*), FE2H on ALBERT (1), AMGN (14) |
| 3    | Longformer (23), HGN (33), IRC (61), gold-answers-random-facts (*)     |
| 4    | S2G-large (29), Text-CAN (45)                                         |
| 5    | SAE (46), GRN (63)                                                    |
| 6    | DecompRC (unranked)                                                   |
| 7    | random-answers-random-facts (*)                                        |

rank 61) are also located in the first Pareto front which means that they also possess a combination of strengths that dominates the models in the other ranks. Table 2 shows the leaderboard based on automatic proxy scores. The gold prediction system is the single winner in this leaderboard, followed by the two real models FE2H on ALBERT and AMGN. While the first models are ordered consistently with the HotpotQA leaderboard, the Pareto front leaderboards disagree w.r.t. ranks for others, e.g., the IRC model (leaderboard rank 61), Longformer (leaderboard rank 23) or S2G-large (leaderboard rank 29). For the synthetic systems, we observe differences across the two Pareto front leaderboards. For example, the gold-answers-random-facts system is ranked last w.r.t. human ratings but ranked third w.r.t. automatic scores. This highlights that the proxy metrics do not reflect the quality dimensions probed in the human ratings sufficiently well. We provide details on the exact model ratings and proxy scores in the appendix.

6 Conclusion

This paper aims at increasing the awareness of the shortcomings and open challenges that today’s explanation quality evaluation practices face. We discuss general characteristics of explanation quality, describe current practices and point out to which extent they violate those characteristics. Finally, we propose guidelines for a more effective evaluation, which we hope to inspire future work and ultimately drive the field towards reliable and meaningful explanation quality evaluation. Our discussion is backed up with examples, well-known theories and empirical findings from a crowdsourced case study that we conducted for the example of explainable question answering systems.

Limitations

Proposed Guidelines. We discussed the limitations of our proposed guidelines within the main body of the paper. The main aspects are:

- Validation of Proxy Scores: Since the final pool of models for a task or leaderboard will not be available from the beginning, we have to accept a grace period in which we can only assume that the chosen proxy score is valid and measures the desired explanation quality. For the same reason, any metrics used for evaluation needs to be periodically re-tested for its validity. Finally, each validity evaluation is limited to a group of explainees and cannot be taken as a general finding.

- Human Evaluation: User studies require the compensation of participants as well as preparation time to recruit participants and conduct the studies. Furthermore, the results of user studies might be noisy.

- Usage of Different Scores: If multiple scores are used, it might be hard to determine a single “winning” system in an evaluation. For rankings based on Pareto fronts, a large number of scores (in relation to the number of systems) will lead to only few or, in the extreme case, only one Pareto front.

Case Study. We focus our case study on the HotpotQA dataset, which limits the extent to which the empirical support of our theoretical claims can be generalized to the breadth of today’s explainability tasks and applications. Our intention is to provide initial evidence to inspire future work to confirm but also challenge our claims. It is worth noting that we focused on evaluating the output of systems for given dataset instances in our analysis and case study. An arguably more powerful approach would have been to probe the prediction function of the models with presumable different inputs and evaluate their behavior (similar to the FaRM score from Schuff et al. (2020)). While we argue that the principles we discussed in our paper can also be applied to such an evaluation, we could not analyze it empirically due to limited access to the HotpotQA leaderboard models.

Furthermore, the current version of our case study does not allow us to compare across different user groups (e.g., high-school students vs. machine-learning experts). We leave this to future work.
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A HotpotQA

In this section, we provide more details on the HotpotQA task and leaderboard.

A.1 Task

In HotpotQA (Yang et al., 2018), systems receive a question and parts of ten Wikipedia articles as context and have to predict (i) an answer to the question (yes/no or a span from the context) as well as (ii) which sentences from the context are supporting facts to their predicted answer. The supporting facts serve as an explanation for the predicted answer of the model. The HotpotQA dataset provides gold annotations for answers as well as supporting facts for 113k instances in total. The training and development splits of the dataset are publicly available while the test set is only used for the leaderboard.

A.2 Leaderboard and Scores

The HotpotQA leaderboard reports the metrics exact match (EM), precision, recall and F1 for three levels: (i) the answer, (ii) the supporting facts, and (iii) a joint definition built on instance-wise products of EM, precision and recall and the derived F1 score. The leaderboard ranks the systems according to joint F1 scores on a non-public test set (breaking ties by using other measures like joint EM and answer F1).

Schuff et al. (2020) additionally propose two scores for the HotpotQA task: (i) answer-explanation consistency based on the fraction of predicted answers that are located in the predicted supporting facts (LocA score) and (ii) model consistency that probes how the model reacts to the removal of facts that it predicted to be (ir)relevant (FaRM score).

B User Study

This section describes further details on the study design, the used models as well as additional results derived from user comments.

B.1 Details on Study Design

Questions. We sample 100 questions from the HotpotQA test set. During the experiment, each participant is shown 25 questions that were randomly sampled from the 100 questions and are ordered randomly to mitigate potential carry-over effects across participants. We make use of this approach to (i) cover a large amount of questions to better reflect the dataset and at the same time (ii) restrict the user’s workload to evade fatigue effects.

Human Ratings. We collect per-instance participant ratings of perceived answer correctness (“The answer is correct.”), explanation utility (“The explanation helps me to decide if the answer is correct.”), and explanation consistency (“The explanation helps me to understand how the model came up with its answer.”). In addition, we track the completion time, the participants take to finish each instance. Further, we collect overall ratings within a post questionnaire at the end of the experiment. We ask participants to rate usability using the UMUX questionnaire (Finstad, 2010, 2013) and mental effort using the Paas scale (Paas, 1992).

Figures 6 and 7 provide screenshots of the questionnaires.

Experiment Design. We make use of an in-between subject experiment design, i.e., each participant is exposed to model predictions from exactly one model. We recruit five participants from Mechanical Turk for each model. We include two attention checks to filter out participants that do not read the question or the explanations.

Models. We obtained consent from submitters of 24 models to include the system predictions in our analysis. From those 24 models, we choose 10 models for our user study: AMGN (14) (anonymous), FE2H on ALBERT (1) (Li et al., 2022), HGN (Fang et al., 2020) (33), IRC (61) (Nishida et al., 2021), Longformer (23) (anonymous), S2G-large (29) (anonymous), Text-CAN (45) (Usyd NLP), GRN (63) (anonymous), SAE (46) (Tu et al., 2020), DecompRC (unranked) (Min et al., 2019).

Additionally, we derive five synthetic models to include extreme cases of the potential space of systems: (i) Gold answers and gold facts: Plain gold annotations, (ii) Gold answers and random...
Figure 6: MTurk interface to rate a system prediction.

| Question | System answer: alcohol from grain |
|----------|----------------------------------|
| System explanation: | house |
| - Ethanol is usually distilled from grain (usually wheat or rye) though it can exceptionally also be distilled from potatoes, honey, sugar beets etc. | |
| - A type of food adds the following components to the meal: protein (animal or plant), carbohydrate, fiber, fat, and water. | |

Please rate the following statements.

| The answer is correct. | 
|------------------------|------------------------|
| strongly disagree | 1 2 3 4 5 6 7 strongly agree |
| The explanation helps me to decide if the answer is correct. | 
| strongly disagree | 1 2 3 4 5 6 7 strongly agree |
| The explanation helps me to understand how the model came up with its answer. | 
| strongly disagree | 1 2 3 4 5 6 7 strongly agree |

Do you have any additional comments?

Figure 7: Post questionnaire of the MTurk interface.
facts: Gold answers with random facts. We sample the same number of facts as the gold annotations, but do not sample from the articles in which the gold facts are located in. (iii) Random answers and gold facts: We sample a random answer from the context while keeping the number of words the same as the gold answer, (iv) Random answers and random facts: Both answers and facts are sampled, as described before, (v) Gold answers and all facts: Gold answers but the predicted facts are all facts from the context (i.e. from 10 Wikipedia articles).

Automatic Scores. Table 3 ranks the 24 models for which we got permission to include them in our analysis in comparison to our five synthetic models that we mainly use for upper bounds and comparison to random predictions.

Figure 9 displays Kendall’s $\tau$ correlations between the automatic scores regarding the analyzed models.

Participants. We collect responses from 75 crowdworkers based in the US. We recruit workers with $>90\%$ approval rate and an MTurk Master qualification and ensure that each worker participates no more than once in our experiments as this would introduce inter-condition dependencies and confound results.

Human Rating Results. Table 4 displays the human ratings and completion times we obtained within the user study for the 10 leaderboard systems as well as our five synthetic systems.

Automatic Scores and Human Ratings. Figure 10 displays the Kendall’s $\tau$ correlations between automatic scores and human ratings. We additionally provide Bonferroni-corrected significance levels. We further evaluate (i) grouped weighted $\kappa$ inter-annotator agreements (IAAs) (Cohen, 1968) as an appropriate IAA measure for ordinal responses and (ii) standard deviations to provide an additional perspective on the ratings’ variances. We observe $\kappa = 0.42 / SD= 0.43$ for correctness, $\kappa = 0.3 / SD= 1.88$ for utility and $\kappa = 0.33 / SD= 2.13$ for consistency. These IAA and standard deviations signal a low agreement / high variability which is commonly interpreted to correspond to low-quality annotations. However, we want to emphasize that the purpose of our study is not (and should not be) to collect clean annotations of specific explanation instances but instead to capture the relation between automatic scores and intentionally and potentially noisy subjective human ratings as these are the exact ratings that constitute human assessment of explanation quality.

Question Pool Size Simulations. In order to support our assumption that our pool of 100 questions is sufficiently representative, we simulate experiments with various question subsets. Figure 8 shows that correlations already stabilize for 20 questions and that there are no qualitative or quantitative differences to using 100 (all $\tau$ differences $\leq 0.04$).

Further Findings from User Comments. Besides the points mentioned in the main body of the paper, we find the following free-text user comments especially interesting:

- “I see why the model thought it, but it doesn’t provide any useful info in reality”. This comment shows that users actually have the impression that a model “thinks”, even if it does not perform the task well.
- “The question asks about two players but there is only a correct answer for one player and only one explanation”. This comment confirms that one type of model error is to provide answers that do not semantically match the question.
- “Seems like an error because the explanation doesn’t seem related to the answer and the answer is unfinished”.
- “It doesn’t really state how it came up with this answer, as it only told about other fights. My default answer is incorrect, until the system proves it to be true.”

We note that this interpretation can be challenged and low IAAs are not necessary to collect highly reliable data (Beigman Klebanov and Beigman, 2009).
Figure 8: Kendall’s τ correlation coefficients between different human ratings and joint-F1.

| Model             | Joint-F1 | Answer-F1 | SP-F1 | LocA  | # words | # facts |
|-------------------|----------|-----------|-------|-------|---------|---------|
| * gold            | 0.9999   | 0.9999    | 1.0000| 0.9980| 58.4296 | 2.4305  |
| fe2h_albert       | 0.7654   | 0.8444    | 0.8914| 0.9823| 56.0451 | 2.3020  |
| amgn_plus         | 0.7525   | 0.8338    | 0.8883| 0.9596| 56.4771 | 2.3291  |
| fe2h_electra      | 0.7491   | 0.8269    | 0.8872| 0.9860| 55.7048 | 2.2872  |
| s2g_plus          | 0.7436   | 0.8217    | 0.8873| 0.1261| 55.5947 | 2.2758  |
| hgn_large         | 0.7422   | 0.8220    | 0.8848| 0.9719| 55.9020 | 2.3045  |
| amgn              | 0.7420   | 0.8280    | 0.8812| 0.9547| 54.0543 | 2.2154  |
| git               | 0.7387   | 0.8201    | 0.8819| 0.9691| 56.7310 | 2.3357  |
| ftrreader_large   | 0.7379   | 0.8216    | 0.8843| 0.9203| 56.3926 | 2.3213  |
| longformer        | 0.7317   | 0.8126    | 0.8834| 0.7154| 56.4994 | 2.3255  |
| hgn_roberta_large | 0.7258   | 0.8062    | 0.8761| 0.9829| 57.2278 | 2.3661  |
| text_can_large    | 0.7253   | 0.8080    | 0.8696| 0.9519| 56.1457 | 2.3049  |
| s2g_large         | 0.7226   | 0.8024    | 0.8761| 0.1194| 55.8983 | 2.3055  |
| sae_large         | 0.7145   | 0.7963    | 0.8687| 0.9583| 56.2038 | 2.3067  |
| hgn               | 0.7104   | 0.7937    | 0.8733| 0.9682| 57.3562 | 2.3606  |
| s2g_base          | 0.6952   | 0.7703    | 0.8720| 0.1233| 56.4389 | 2.3271  |
| text_can          | 0.6596   | 0.7399    | 0.8576| 0.9212| 56.6486 | 2.3294  |
| sae               | 0.6292   | 0.7277    | 0.8282| 0.8645| 57.4972 | 2.3773  |
| grn_update        | 0.6173   | 0.7023    | 0.8420| 0.8493| 52.1172 | 2.1249  |
| mkgn              | 0.6169   | 0.7069    | 0.8354| 0.7238| 54.2208 | 2.2308  |
| qfe               | 0.5962   | 0.6806    | 0.8450| 0.8708| 54.6789 | 2.2408  |
| irc               | 0.5922   | 0.7253    | 0.7936| 0.7686| 70.3375 | 2.9413  |
| grn               | 0.5848   | 0.6672    | 0.8411| 0.8886| 57.3488 | 2.3715  |
| kgnn              | 0.5282   | 0.6575    | 0.7680| 0.8608| 55.6323 | 2.3449  |
| decomprecomb (unranked) | –       | 0.6977    | –     | –     | –       | –       |
| * gold-answers-all-facts | 0.1179 | 0.9999   | 0.1180| 0.9980| 923.9561| 41.2556 |
| * random-answers-gold-facts | 0.0193 | 0.0193  | 1.0000| 0.1205| 58.4296 | 2.4305  |
| * random-answers-random-facts | 0.0000 | 0.0189  | 0.0000| 0.1070| 55.9535 | 2.4255  |
| * gold-answers-random-facts | 0.0000 | 0.9999  | 0.0000| 0.0322| 55.8294 | 2.4255  |

Table 3: Extended HotpotQA leaderboard including synthetic systems derived from the gold test set (marked by with “*” and italics).
| System                          | UMUX  | Consistency | Utility | Answer Correctness | Mental Effort | Completion Time |
|--------------------------------|-------|-------------|---------|--------------------|---------------|-----------------|
| amgn                           | 86.666667 | 5.792       | 5.640   | 1.840              | 5.8           | 80.172512       |
| decomprecomb                   | 78.333333 | 4.984       | 4.848   | 1.736              | 5.8           | 43.166416       |
| fc2h_albert                    | 97.500000 | 6.256       | 6.152   | 1.880              | 4.0           | 81.833992       |
| gold                           | 83.333333 | 6.120       | 6.192   | 1.960              | 5.6           | 41.370616       |
| gold_answers_all_facts         | 85.833333 | 5.024       | 5.576   | 1.300              | 5.8           | 75.355080       |
| gold_answers_random_facts      | 15.833333 | 2.280       | 2.352   | 1.736              | 7.8           | 43.833464       |
| grn                            | 68.333333 | 5.400       | 5.792   | 1.712              | 4.8           | 75.057856       |
| hgn                            | 90.000000 | 6.280       | 6.304   | 1.864              | 4.2           | 64.419888       |
| irc                            | 83.333333 | 5.976       | 6.336   | 1.808              | 5.8           | 118.040632      |
| longformer                     | 86.666667 | 5.944       | 6.272   | 1.864              | 5.0           | 42.020144       |
| random_answers_gold_facts      | 20.833333 | 2.056       | 2.912   | 1.040              | 4.6           | 44.400432       |
| random_answers_random_facts    | 23.333333 | 2.432       | 2.912   | 1.024              | 5.2           | 48.699904       |
| s2g_large                      | 88.333333 | 6.088       | 6.144   | 1.848              | 4.0           | 50.889392       |
| sae                            | 86.666667 | 5.848       | 6.296   | 1.816              | 4.2           | 86.633512       |
| text_can                       | 86.666667 | 5.984       | 6.264   | 1.896              | 4.6           | 94.164544       |

Table 4: Human ratings of the systems we assessed within our human evaluation (synthetic systems are marked by with “∗” and italics).

![Kendall’s τ correlation coefficients between automatic automatic scores to quantifying model behaviour related to explanation quality on the HotpotQA dataset. Significance levels are corrected using Bonferroni correction (∗: $p \leq 0.05$, **: $p \leq 0.01$, ***: $p \leq 0.001$ and ****: $p \leq 0.0001$).](image-url)
|          | answer EM | answer F1 | answer prec | answer recall | SP EM | SP F1 | SP prec | SP recall | joint EM | joint F1 | joint prec | joint recall | #words | #facts | LocA |
|----------|-----------|-----------|-------------|--------------|-------|-------|---------|-----------|----------|----------|------------|--------------|--------|--------|------|
|          | 0.29      | 0.29      | 0.29        | 0.29         | 0.25  | 0.25  | 0.23    | 0.25      | 0.45     | 0.50     | 0.49       | 0.49          | 0.06   | -0.22  | 0.40 |
|          | (‘)       | (‘)       | (‘)         | (‘)          | (‘)   | (‘)   | (‘)     | (‘)       | (‘)      | (‘)      | (‘)        | (‘)           |        |        |      |
|          | 0.37      | 0.38      | 0.38        | 0.38         | 0.34  | 0.35  | 0.31    | 0.33      | 0.48     | 0.56     | 0.50       | 0.49          |        |        |      |
|          | (‘‘‘)     | (‘‘‘)     | (‘‘‘)       | (‘‘‘)        | (‘‘‘) | (‘‘‘) | (‘‘‘)   | (‘‘‘)     | (‘‘‘)    | (‘‘‘)    | (‘‘‘)      | (‘‘‘)         |        |        |      |
|          | 0.03      | 0.05      | 0.05        | 0.05         | 0.09  | 0.08  | 0.09    | 0.01      | 0.03     | 0.00     | 0.03       | 0.03          |        |        |      |
|          | 0.02      | 0.03      | 0.03        | 0.03         | 0.22  | 0.22  | 0.20    | 0.09      | 0.21     | 0.19     | 0.19       | 0.10          |        |        |      |
|          | -0.11     | -0.11     | -0.11       | -0.11        |        |        |         |          | -0.12    | -0.05    | -0.12      |                |        |        |      |
|          | 0.50      | 0.50      | 0.50        | 0.50         | 0.50  | 0.50  | 0.50    | 0.50      | 0.50     | 0.50     | 0.50       | 0.50          |        |        |      |
|          | 0.40      | 0.34      | 0.38        | 0.25         | 0.40  | 0.34  | 0.38    | 0.25      | 0.40     | 0.34     | 0.38       | 0.25          |        |        |      |
|          | 0.34      | 0.38      | 0.38        |             |        |        |         |          |          |          |             |                |        |        |      |
|          | 0.25      | 0.25      | 0.25        |             |        |        |         |          |          |          |             |                |        |        |      |

Figure 10: Kendall’s τ correlations (per HIT). Significance levels are corrected using Bonferroni correction (*: p ≤ 0.05, **: p ≤ 0.01, ***: p ≤ 0.001 and ****: p ≤ 0.0001).