The Disagreement Problem in Explainable Machine Learning: A Practitioner's Perspective

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Abstract

As various post hoc explanation methods are increasingly being leveraged to explain complex models in high-stakes settings, it becomes critical to develop a deeper understanding of if and when the explanations output by these methods disagree with each other, and how such disagreements are resolved in practice. However, there is little to no research that provides answers to these critical questions. In this work, we introduce and study the *disagreement problem* in explainable machine learning. More specifically, we formalize the notion of disagreement between explanations, analyze how often such disagreements occur in practice, and how practitioners resolve these disagreements. To this end, we first conduct interviews with data scientists to understand what constitutes disagreement between explanations (feature attributions) generated by different methods for the same model prediction, and introduce a novel quantitative framework to formalize this understanding. We then leverage this framework to carry out a rigorous empirical analysis with four real-world datasets, six state-of-the-art post hoc explanation methods, and eight different predictive models, to measure the extent of disagreement between the explanations generated by various popular post hoc explanation methods. In addition, we carry out an online user study with data scientists to understand how they resolve the aforementioned disagreements. Our results indicate that state-of-the-art explanation methods often disagree in terms of the explanations they output. Worse yet, there do not seem to be any principled, well-established approaches that machine learning practitioners employ to resolve these disagreements, which in turn implies that they may be relying on misleading explanations to make critical decisions such as which models to deploy in the real world. Our findings underscore the importance of developing principled evaluation metrics that enable practitioners to effectively compare explanations.

1. Introduction

As machine learning (ML) models are increasingly being deployed to make consequential decisions in domains such as healthcare, finance, and policy, there is a growing emphasis on ensuring that these models are interpretable to ML practitioners and other domain experts (e.g., doctors, policy makers). In order to assess when and how much to rely on these models, and detect systematic errors and potential biases in them, practitioners often seek to understand the behavior of these models (Doshi-Velez and Kim, 2017). However, the increasing complexity, as well as the proprietary nature of predictive models, make it challenging to understand these complex black boxes, and thus motivate the need for tools and techniques that can explain them in a faithful and human interpretable manner. To this end, several techniques have been proposed in recent literature to explain complex models in a *post hoc* fashion (Ribeiro et al., 2016a; Lundberg and Lee, 2017a; Simonyan et al., 2014; Sundararajan et al., 2017; Selvaraju et al., 2017; Smilkov et al., 2017). Most of the popular *post hoc explanation methods* focus on explaining individual predictions (i.e., local explanations) of any given model, and can be broadly categorized into *perturbation-based* (e.g., LIME, SHAP (Ribeiro et al., 2016b; Lundberg and Lee, 2017a)) and *gradient-based* (e.g., Gradient times Input, SmoothGrad, Integrated Gradients, GradCAM (Simonyan et al., 2014; Sundararajan et al., 2017; Selvaraju et al., 2017; Smilkov et al., 2017)) methods.

While prior research has taken first steps towards analyzing the behavior of explanation methods (Liu et al., 2021; Petsiuk et al., 2018; Slack et al., 2021; Zhou et al., 2021; Hooker et al., 2018; Ghorbani et al., 2019; Slack et al., 2020; Aivodji et al., 2019), several critical aspects of these meth-

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Workshop on Interpretable ML in Healthcare at International Conference on Machine Learning (ICML),

ods remain unexplored. For instance, ML practitioners do not typically rely on a single explanation method, but instead employ multiple methods simultaneously to understand the rationale behind individual model predictions (Kaur et al., 2020). While ML practitioners can obtain a coherent understanding of model behavior if multiple methods generate consistent explanations, there may be instances for which explanations generated by various methods disagree. When faced with such a *disagreement problem*, practitioners need to decide which explanation to rely on. The extent to which this disagreement problem occurs in practice is unclear because there is little to no research on understanding how often explanations produced by state-of-the-art methods disagree with each other. Furthermore, if and when the disagreement problem occurs, practitioners need to tackle it carefully, otherwise they may end up relying on misleading explanations, which may, in turn, lead to catastrophic consequences – e.g., trusting and deploying racially-biased models, trusting incorrect model predictions and recommending sub-optimal treatments to patients, etc. (Slack et al., 2020). However, the lack of reliable, general purpose evaluation metrics which can ascertain and compare the quality of explanations pose a serious challenge to addressing the disagreement problem in practice. Given all the above, it is critical to not only understand and quantify how often explanations output by state-of-the-art methods disagree with each other, but also study how such disagreements are resolved by ML practitioners. However, there is no existing work that focuses on these important aspects.

We address the aforementioned gaps by introducing and studying the *disagreement problem* in explainable ML. To the best of our knowledge, this work is the first to highlight the disagreement problem, determine the extent to which it occurs in the real world, and understand how it is being resolved in practice. We make the following key contributions:

a) We first obtain practitioner input on what constitutes explanation disagreement, and the extent to which they encounter this problem in their day-to-day workflow. To this end, we conduct semi-structured interviews[1] with data scientists (N = 25) who regularly work with explainability tools. Note that our work focuses on local explanation methods that output feature attributions such as LIME, SHAP, and gradient-based methods.

b) Using insights from these interviews, we formalize the notion of explanation disagreement, and propose a novel evaluation framework to quantitatively measure disagreement between any two explanations of the same prediction.

c) We leverage the framework above to carry out a rigorous empirical analysis with real-world data to quantify the level of disagreement between popular post hoc explanation methods. We experiment with four real-world datasets, six state-of-the-art explanation methods, and various popular predictive models.

d) Lastly, we study how explanation disagreements are resolved in practice. We carry out an online user study with data scientists (N = 25) where we show them pairs of disagreeing explanations, and ask them which explanation (if any) would they rely on and why. We also ask them to provide a high-level description of the strategies they use to resolve explanation disagreements in their day-to-day workflow.

Results from our empirical analysis, user interviews and studies indicate that state-of-the-art explanation methods often disagree in terms of the explanations they output, and worse yet, there do not seem to be any principled, well established approaches that ML practitioners employ to resolve these disagreements. Specifically, 84% of interview participants reported encountering the disagreement problem in their day-to-day workflow. Our empirical analysis further confirmed that explanations generated by state-of-the-art methods often disagree with each other, and this phenomenon persists across various model classes and data modalities. Furthermore, 86% of online user study responses indicated that ML practitioners either employed arbitrary heuristics (e.g., choosing a favorite method) or simply did not know how to resolve the disagreement problem. Our findings not only shed light on the previously unexplored disagreement problem, but also underscore the importance of developing principled evaluation metrics to effectively compare explanations, and educating practitioners about the same.

Related Work Our work builds on the vast literature in explainable ML. Prior works have developed state-of-the-art explanation methods (Ribeiro et al., 2016a; Lundberg and Lee, 2017b; Slack et al., 2021; Ribeiro et al., 2018; Simonyan et al., 2014; Sundararajan et al., 2017; Selvaraju et al., 2017; Smilkov et al., 2017), investigated the quality of explanations generated by these methods (Liu et al., 2021; Petsiuk et al., 2018; Slack et al., 2021; Zhou et al., 2021;?; Carvalho et al., 2019; Gilpin et al., 2018; Liu et al., 2021), and studied how well humans can understand these explanations (Doshi-Velez and Kim, 2017; Kaur et al., 2020; Bhatt et al., 2020; Hong et al., 2020). However, to our knowledge, previous works have not studied the extent to which explanations generated by state-of-the-art explanation methods disagree, developed an evaluation framework to quantitatively measure disagreement among explanations, nor examined how disagreements are resolved in practice. For a more detailed discussion of prior works and their connections to this research, see Appendix A.

[1]All the user interviews and studies in this work were approved by our institution's IRB.

2. Understanding and Measuring Disagreement between Model Explanations

In this section, we discuss practitioner perspectives on what constitutes disagreement between two explanations, and formalize the notion of explanation disagreement by proposing a novel evaluation framework to quantitatively measure the disagreement between any two explanations.

2.1. Characterizing Explanation Disagreement Using Practitioner Inputs

Here, we describe the study conducted with data scientists to characterize explanation disagreement, and outline our findings and insights from this study.

2.1.1. Interviews with Practitioners: Study Details

We conducted 30-minute long semi-structured interviews with 25 data scientists who regularly use explainability techniques (demographic details in Appendix B.1). Interviews included, but were not limited to, the following questions: Q1) *How often do you use multiple explanation methods to understand the same model prediction?* Q2) *What constitutes disagreement between two explanations that explain the same model prediction?* Q3) *How often do you encounter disagreements between explanations output by different methods for the same model prediction?*

2.1.2. Findings and Insights

Our study revealed a wealth of information about how data scientists utilize explanation methods and their perspectives on disagreement between explanations. 22 out of the 25 participants (88%) said that they almost always use multiple explanation methods to understand the same model prediction. Furthermore, 21 out of the 25 participants (84%) mentioned that they often run into some form of disagreement between explanations generated by different methods for the same prediction. They also elaborated on when they think two explanations disagree:

Top features are different: Most popular post hoc explanation methods return a feature importance value for each feature. These values indicate which features contribute most (either positively or negatively) to the prediction. 21 out of the 25 participants (84%) mentioned that such a set of top features is *"the most critical piece of information"* that they rely on. They also noted that they typically look at the top 5 to 10 features provided by an explanation for each prediction. When two explanations have different sets of top features, they consider it to be a disagreement.

Ordering among top features is different: 18 out of 25 participants (72%) indicated that they also consider the ordering among the top features very carefully in their workflow. Therefore, they consider a mismatch in the ordering of the top features provided by two different explanations to be a disagreement.

Direction of top feature contributions is different: 19 out of 25 participants (76%) mentioned that the *sign* or *direction* (positive or negative) of the feature contribution is also critical. Any mismatch in the signs of the top features between two explanations is a disagreement. As one participant remarked, "*I saw an explanation indicating that a top feature bankruptcy contributes positively to a particular loan denial, and another explanation saying that it contributes negatively. That is a clear disagreement.*".

Relative ordering of certain features is different: 16 participants (64%) indicated that they also look at relative ordering of features of interest; and if explanations provide contradicting information, then they disagree. As one participant remarked, *"I often check if salary is more important than credit score in loan approvals. If one explanation says salary is more important than credit score, and another says credit score is more important than salary; then it is a disagreement."*

A striking finding from our study is that participants typically characterize explanation disagreement based on factors such as mismatch in top features, feature ordering, and directions of feature contributions, but not on the feature importance values output by different explanation methods. 24 out of 25 participants (96%) opine that feature importance values output by different explanation methods are not directly comparable, so they do not base explanation disagreement on these values not being similar. One participant succinctly summarized practitioners' perspective on the explanation disagreement problem – *"The values generated by different explanation methods are clearly different. So, I would not characterize disagreement based on that. But, I would at least want the explanations they output to give me consistent insights. The explanations should agree on what are the most important features, the ordering among them and so on for me to derive consistent insights. But, they don't!"*

2.2. Formalizing the Notion of Explanation Disagreement

Our study indicates that ML practitioners consider the following key aspects when they think about explanation disagreement: a) the extent to which explanations differ in the top-k features, the signs (directions of contribution) and the ordering of these top-k features, and b) the extent to which explanations differ in the relative ordering of certain features of interest. To formalize these intuitions, we propose six metrics: *feature agreement*, *rank agreement*, *sign agreement*, *signed rank agreement*, *rank correlation*, and *pairwise rank agreement*. The first four metrics capture disagreement w.r.t. the top-k features of the explanations, while the last two metrics capture disagreement w.r.t. a selected set of features. For all six metrics, lower values indicate stronger disagreement.

2.2.1. MEASURING DISAGREEMENT W.R.T. TOP-K FEATURES

We now define four metrics, which capture specific aspects of explanation disagreement w.r.t. the top-k features.[2]

Feature Agreement: ML practitioners in our study (Section 3.1) clearly indicated that a key notion of disagreement between a pair of explanations is that they output different top-k features. To capture this notion, we introduce the feature agreement metric which computes the fraction of common features between the sets of top-k features of two explanations. Given two explanations E_a and E_b, the Feature Agreement(FA) metric is formally defined as:

$$FA(E_a, E_b, k) = \frac{|top\_features(E_a, k) \cap top\_features(E_b, k)|}{k} \tag{1}$$

where $top\_features(E, k)$ returns the set of top-k features (based on the magnitude of the feature importance values) of the explanation E. If the sets of top-k features of explanations E_a and E_b match, then $FA(E_a, E_b, k) = 1$.

Rank Agreement: Practitioners in our study also indicated that if the ordering of the top-k features is different for two explanations (even if the feature sets are the same), then they consider it to be a disagreement. To capture this notion, we introduce the rank agreement metric which computes the fraction of features that are not only common between the sets of top-k features of two explanations, but also have the same position in the respective rank orders. Rank agreement is a stricter metric than feature agreement since it also considers the ordering of the top-k features. Given two explanations E_a and E_b, the $RankAgreement(E_a, E_b, k)$ is formally defined as:

$$\frac{|\bigcup_{s \in S} \{s \mid s \in top\_features(E_a, k) \wedge s \in top\_features(E_b, k) \wedge rank(E_a, s) = rank(E_b, s)\}|}{k} \tag{2}$$

where S is the complete set of features in the data, $top\_features(E, k)$ is defined as above, and $rank(E, s)$ returns the position (or rank) of the feature s according to the explanation E. If the rank-ordered lists of top-k features of explanations E_a and E_b match, then $RankAgreement(E_a, E_b, k) = 1$.

Sign Agreement: Practitioners also mentioned that they consider two explanations to disagree if the feature attribution signs (directions of feature contribution) do not align for the top-k features. To capture this notion, we introduce the sign agreement metric which computes the fraction of features that are not only common between the sets of top-k features of two explanations, but also share the same attribution sign in both explanations. Sign agreement is a stricter metric than feature agreement since it also considers attribution signs of the top-k features. More formally, $SignAgreement(E_a, E_b, k)$ is defined as:

where $sign(E, s)$ returns the sign (direction of contribution) of the feature s according to the explanation E.

Signed Rank Agreement: This metric fuses together all the above notions, and computes the fraction of features that are not only common between the sets of top-k features of two explanations, but also share the same feature attribution sign (direction of contribution) and position (rank) in both explanations. Signed rank agreement is the strictest compared to all the aforementioned metrics since it considers both the ordering and the attribution signs of the top-k features. More formally, $SignedRankAgreement(E_a, E_b, k)$ is formulated as:

$$\frac{|\bigcup_{s \in S} \{s \mid s \in top\_features(E_a, k) \wedge s \in top\_features(E_b, k) \wedge sign(E_a, s) = sign(E_b, s) \wedge rank(E_a, s) = rank(E_b, s)\}|}{k}$$

where $top\_features$, $sign$, $rank$ are all as defined above. $SignedRankAgreement(E_a, E_b, k) = 1$ if the top-k features of two explanations match on all aspects (i.e., features, feature attribution signs, rank ordering) barring the exact feature importance values.

2.2.2. MEASURING DISAGREEMENT W.R.T. FEATURES OF INTEREST

Practitioners also indicated that they consider two explanations to disagree if their relative ordering of features of interest differ. To formalize this notion, we introduce the two metrics below.

Rank Correlation: We adopt a standard rank correlation metric (i.e., Spearman's rank correlation coefficient) to measure the agreement between feature rankings provided by two explanations for a selected set of features. In practice, this selected set of features corresponds to features that are of interest to end users, and can be provided as input by end

[2] The top-k features of an explanation are typically computed only based on the magnitude of the feature importance values and not the signs.

users. Given two explanations E_a and E_b, rank correlation can be computed as:

$$r_s(Ranking(E_a, F), Ranking(E_b, F))$$

where F is a selected set of features provided by an end user, r_s computes Spearman's rank correlation coefficient, and $Ranking(E, F)$ assigns ranks to features in F based on explanation E.

Pairwise Rank Agreement: Pairwise rank agreement takes as input a set of features that are of interest to the user, and captures if the relative ordering of every pair of features in that set is the same for both the explanations i.e., if feature A is more important than B according to one explanation, then the same should be true for the other explanation. This metric computes the fraction of feature pairs for which the relative ordering is the same between two explanations. More formally, we formulate Pairwise Rank Agreement as :

$$\frac{\sum_{i,j \text{ for } i<j} \mathbb{1}[RelativeRanking(E_a, f_i, f_j) = RelativeRanking(E_b, f_i, f_j)]}{\binom{|F|}{2}}$$

where $F = \{f_1, f_2 \cdots\}$ is a selected set of features input by an end user, $RelativeRanking(E, f_i, f_j)$ is an indicator function which returns 1 if feature f_i is more important than feature f_j according to explanation E, and 0 otherwise.

3. Empirical Analysis of Explanation Disagreement

We leverage the metrics outlined in Section 3 and conduct a comprehensive empirical analysis with six state-of-the-art explanation methods and four real-world datasets to study the explanation disagreement problem.

3.1. Experimental Setup

To carry out our empirical analysis, we leverage four real-world datasets spanning three data modalities: Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) dataset (com, 2016) and German Credit dataset (ger, 1994) (tabular), Antonio Gulli (AG)'s corpus of news articles (AG_News) (ag, 2004) (text), and ImageNet$-1k$ (Russakovsky et al., 2015; ima, 2015) object recognition dataset (images). For dataset details, see Appendix C.1.

We train various models on the data. For tabular data, we train four models: logistic regression, feed-forward neural network, random forest, and gradient-boosted tree. For text data, we train an LSTM-based text classifier. For image data, we use the pre-trained ResNet-18 (He et al., 2016). Next, to explain model predictions for a test set, we apply six state-of-the-art post hoc explanation methods: LIME (Ribeiro et al., 2016c), KernelSHAP (Lundberg and Lee, 2017a), Vanilla Gradient (Simonyan et al., 2014), Gradient times Input (Shrikumar et al., 2017), Integrated Gradients (Sundararajan et al., 2017), and SmoothGrad (Smilkov et al., 2017) (implementation details in Appendix C.3). Then, we evaluate (dis)agreement among explanation methods using the metrics in Section 2.2 (implementation details in Appendix C.4).

3.2. Results and Insights

Explanation methods show disagreement. For example, for tabular data, for the neural network trained on the COMPAS dataset, they show moderate pairwise rank agreement and feature agreement, and weak rank correlation, rank agreement, sign agreement, and signed rank agreement at top-five features (Figure 1). Not only do explanation methods disagree, but there are also varying degrees of disagreement among method pairs. For example, for the same model, rank correlation varies widely across method pairs, with most method pairs even exhibiting negative rank correlation (Figure 23, left). In addition, across all metrics, values of k, and models, some method pairs (Grad-SmoothGrad and Grad*Input-IntGrad) exhibit strong agreement while certain others (Grad-IntGrad, Grad-Grad*Input, SmoothGrad-Grad*Input, and SmoothGRAD-IntGrad) exhibit strong disagreement (Figure 1, Appendix D.1).

Explanation methods tend to display stronger disagreement for the German Credit dataset than for the COMPAS dataset (Appendix D.1 and 12), perhaps be due to the former having more features and slightly lower model performance. They show similar or stronger levels of disagreement for the neural network than for logistic regression across metrics and values of k, for both datasets (Figures 1, 12 and 4, Appendix D.1). In addition, they show similar levels of disagreement for the random forest and gradient-boosted tree models. These trends suggest that disagreement among explanation methods may increase with model complexity. We observe similar disagreements for text and image datasets (see Appendix D.3).

4. Resolving the disagreement problem in practice: a qualitative study

To understand how practitioners resolve the disagreement problem, we conduct a qualitative user study targeted towards explainability practitioners. We now describe our user study design and discuss our findings.

4.1. User Study Design

In total, 25 participants participated in our study, 13 from academia and 12 from industry. Participants from academia were graduate students, and postdoctoral researchers, while participants from industry were data scientists and ML engineers from three different firms. 20 of these participants

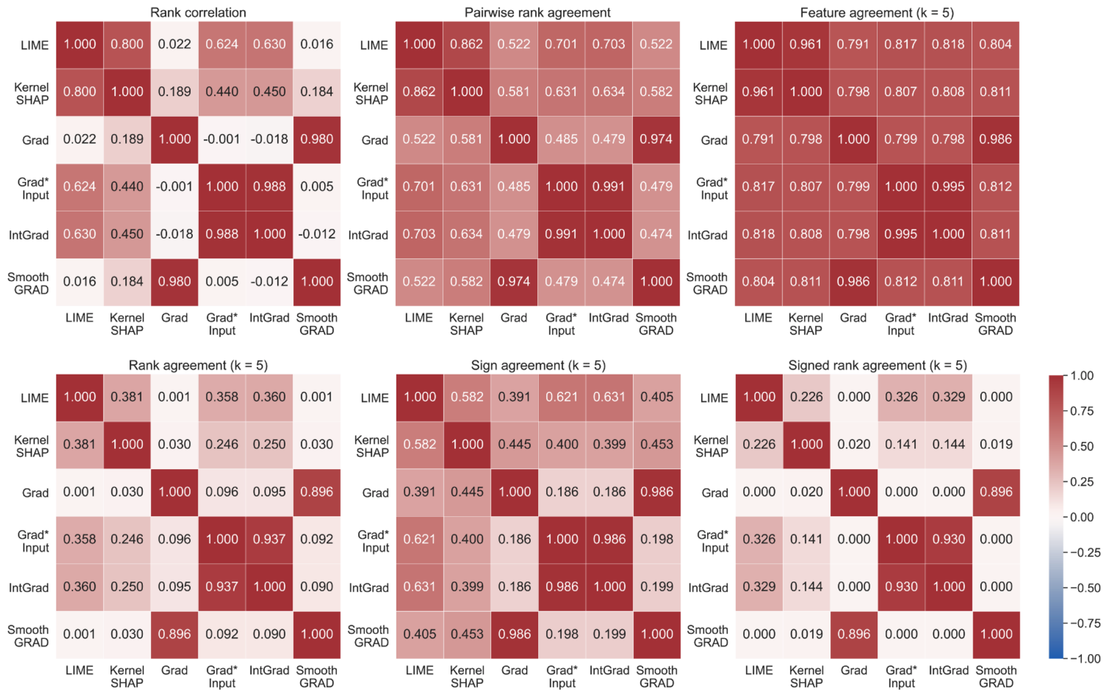
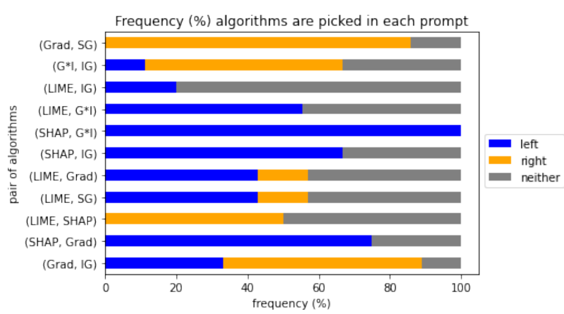
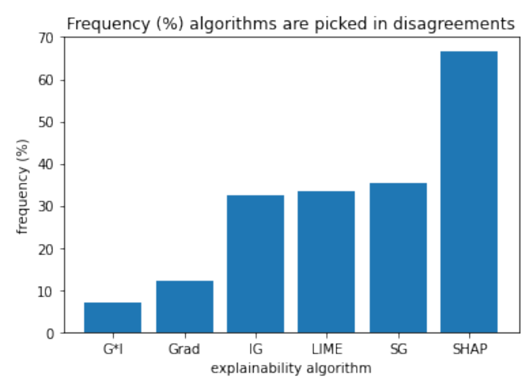


Figure 1: Disagreement between explanation methods for neural network model trained on COMPAS dataset measured by six metrics: rank correlation and pairwise rank agreement across all features, and feature, rank, sign, and signed rank agreement across top $k = 5$ features. Heatmaps show the average metric value over test set data points for each pair of explanation methods, with lighter colors indicating stronger disagreement. Across all six heatmaps, the standard error ranges between 0 and 0.009.



((a)) The frequency with which each of the explanations in a pair is selected upon disagreement. The blue, gold, and grey bars show the percentage of participants (X axis) that picked the left, right, and neither method when presented with the pair of methods shown on the Y axis.



((b)) The frequency with which each of the explanations was chosen when there is a disagreement. X axis indicates the explanation method and Y axis indicates the frequency.

Figure 2: Sub-figures highlight which methods participants chose when the explanations they were shown disagreed. In (a), we show how participants resolved each particular prompt. In (b), we show the frequencies with which each explanation method was selected.

indicated that they have used explanation methods in their work in a variety of ways, including doing research, helping clients explain their models, and debugging their own models. Following the setup in Section 3, we asked participants to compare the output of five pairs of explanation methods on the predictions made by the neural network we trained on the COMPAS dataset. We chose the COMPAS dataset because it only has 7 features, making it easy for participants to understand the explanations.

First, the participants are shown an information page explaining the COMPAS risk score binary prediction setting and various explanation methods. We indicate that we trained a neural network to predict the COMPAS risk score (low or high) from the seven features. We provide a brief description of each feature and ask participants to assume that the defendant's risk of recidivism is correctly predicted to be high risk. We also summarize the six explanation methods used in the study. A screenshot of this information page is shown in Appendix E.1.

Next, each of the participants is shown a series of 5 prompts (sample shown in Appendix Figure 26). Each prompt presents two explanations of the neural network model's prediction for a particular data point generated using two different explanation methods. Different explanation method pairs were run on different data points, generating a set of 15 prompts for each of the 15 explanation method pairs. These prompts were picked to showcase various levels of agreement. We display the full set of features, showing the feature importance of each feature. Red and blue bars indicate that the feature contributes negatively and positively, respectively, to the predicted class. Participants were first asked *"To what extent do you think the two explanations shown above agree or disagree with each other?"* and given four choices: *completely agree, mostly agree, mostly disagree*, and *completely disagree*. If the participant indicated any level of disagreement (any of the latter 3 choices), we then asked *"Since you believe that the above explanations disagree (to some extent), which explanation would you rely on?"* and presented with three choices: the two explanation methods shown and *"it depends"*. They were then asked to explain their response. Participants were allowed to take as much time as they wanted to complete the study.

4.2. Results and Insights

We now discuss the results and findings from our user study in Sections 4.2.1-4.2.4.

4.2.1. Do practitioners observe disagreements?

We aggregated the responses to the first question in each prompt, *"To what extent do you think the explanations shown above agree or disagree with each other?"*. Overall, 4%, 28%, 50%, and 18% of responses indicate *completely agree*, *mostly agree*, *mostly disagree*, and *completely disagree*, respectively, highlighting that there is significant disagreement among our prompts. See Appendix E.4 for more details.

4.2.2. Are certain explanations favored over others?

Next, since different explanation methods have different levels of popularity, we analyze if certain methods are chosen more often in disagreements. Figure 2(a) shows the distribution of how participants resolved disagreements for each prompt (dropping prompts with 4 or less responses). We first emphasize that there is high variability in how participants chose to resolve disagreements, showing a lack of consensus for the majority of prompts. However, when participants do decide to choose a method rather than abstaining, they often choose the same method. For example, for the Vanilla Gradient vs. SmoothGrad pair (top row in Figure 2(a)), participants either chose SmoothGrad over Vanilla Gradient or chose neither. We also aggregate these choices over all prompts, and in Figure 2(b), we plot how often each of the six explanation methods is chosen, finding that indeed, certain methods were favored over others. While KernelSHAP was chosen 66.7% of the time when there are disagreements, Gradient times Input was only chosen 7.0% of the time. We include a further explanation of why participants chose each of the explanations in Appendix E.5, including quotes from participants that supported each method.

4.2.3. How do practitioners resolve disagreements?

Across all six explanation methods, we find three unifying themes that dictated why participants chose one explanation over the other. We give a high-level description of these themes below, highlighting direct quotes from participants in Table 1.

1. One method is inherently better than the other because of its associated theory or publication time (33%): Participants often indicated preference towards a particular method without referencing the shown explanation citing features such as the paper's publication time (more recent papers are better), the method's theory, and the method's stability.

2. One of the generated explanations matches intuition better (32%): Participants frequently said that one method's explanation aligned with their intuition better, citing the absolute and relative values of specific features as evidence.

3. LIME and SHAP are better because COMPAS dataset comprises of tabular data (23%): Participants said that they mainly used LIME and SHAP for tabular data and commonly cited this as their sole reason.

4.2.4. Experiencing and resolving disagreements in day-to-day work:

After studying how participants characterize disagreement (Section 2.1), we sought to understand their experience with the disagreement problem in their day-to-day work (full set of questions in Appendix E.3). Here, we focus on two crucial questions: *(Q1): Do you observe disagreements between explanations output by state of the art methods in*

Table 1: Themes summarizing how participants decided between explanations when faced with disagreement along with quotes.

Theme Highlighted	Sample Quotes
1. One method's paper/theory suggests that it's inherently better (33%).	• *"I have no reason to believe the gradient holds anywhere other than very locally."* • *"[Integrated Gradients is] more rigorous [than SmoothGrad] based on the paper and axioms"* • *"gradient explanations are more unstable"*
2. One explanation matches intuition better (32%).	• *"seems unlikely that all features contributed to a positive classification"* • *"features such as priors_count and length of stay [are] important for determining"* • *"Gradient*Input only consider[s] sensitive features (age, race) as impactful which could be a sign of a biased underlying data distribution"*
3. LIME/SHAP are better for tabular data (23%).	• *"I use LIME for structured data"* • *"SHAP is more commonly used [than Vanilla Gradient] for tabular data"*

your day to day workflow? and *(Q2): How do you resolve such disagreements in your day to day workflow?*. Of the 25 participants, 19 indicated they were practitioners and have used explanation methods in their work. Of these 19 participants, 14 (74%) responded *"yes"* to (Q1), indicating they encountered explanation disagreement in practice. Of the 5 who responded *"no"*, 3 said they had not paid attention to the issue. Through (Q2), we aimed to uncover how participants resolve the disagreement problem in practice. Of the 14 participants answering *"yes"* to (Q1), their responses to (Q2) can be grouped into 3 categories. 50% had personal heuristics for choosing which methods to use (*"picking their favorite method"*, *"rules of thumb based on results in papers"*). These heuristics varied among participants and included ease of implementation, groundedness of theory, recency of publication, ease of understanding, and documentation of packages. 36% didn't indicate any way to resolve these disagreements, showing confusion and uncertainty (*"no clear answer to me"*). Many of the responses indicated a desire for the research community to help (*"I hope research community can provide some guidance"*). Therefore, we hope that these responses motivate and inspire future work in this direction. The remaining 14% proposed to use other metrics such as fidelity (*"try and use some metric to measure fidelity"*). Further details are in Appendix E.7.

5. Conclusions and Discussion

We introduced and studied the *disagreement problem* in explainable ML. We conducted interviews with data scientists to understand what constitutes disagreement between explanations, introduced a novel quantitative framework to formalize this understanding, leveraged this framework to conduct a rigorous empirical analysis of the disagreement problem, and carried out a user study to understand how explanation disagreements are resolved in practice. Our results indicate that state-of-the-art explanation methods often disagree in their explanations, and worse yet, there does not seem to be any principled approach that ML practitioners employ to resolve these disagreements.

We shed light on a unique problem that poses a critical challenge to adopting post hoc explanations in practice and pave the way for several interesting future research directions. First, it would be interesting to systematically study the reasons behind the occurrence of the explanation disagreement problem. Second, it would be interesting to propose novel approaches to address this problem. One way to do this is to come up with principled evaluation metrics which can help practitioners readily discern a reliable explanation from an unreliable one when there is a disagreement. Third, it would be interesting to rethink the problem of explaining ML models from scratch, and potentially develop a whole new set of algorithms that are built on a common set of guiding principles to avoid these kinds of disagreements. Lastly, it would be incredibly important to regularly educate data scientists and practitioners about state-of-the-art approaches (e.g., novel evaluation metrics) that can be used to evaluate and resolve disagreements between explanations.

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A. Related Works

Inherently Interpretable Models and Post hoc Explanations. Many approaches learn inherently interpretable models for various tasks including classification and clustering. Examples of such models include decision trees, decision lists (Letham et al., 2015), decision sets (Lakkaraju et al., 2016), prototype based models (Bien and Tibshirani, 2009; Kim et al., 2014), and generalized additive models (Lou et al., 2012; Caruana et al., 2015). However, complex models such as deep neural networks often achieve higher accuracy than simpler models (Ribeiro et al., 2016b); thus, there has been a lot of interest in constructing *post hoc explanations* to understand their behavior. To this end, several techniques have been proposed to construct post hoc explanations of complex models. These techniques differ in their access to the complex model (i.e., black box vs. access to internals), the scope of approximation (e.g., global vs. local), search technique (e.g., perturbation-based vs. gradient-based), and basic units of explanation (e.g., feature importance vs. rule-based). For instance, LIME, SHAP, Anchors, BayesLIME and BayesSHAP (Ribeiro et al., 2016a; Lundberg and Lee, 2017b; Slack et al., 2021; Ribeiro et al., 2018) are *perturbation based local* explanations as they leverage perturbations of individual instances to construct interpretable local approximations (e.g., linear models). On the other hand, methods such as Gradient*Input, SmoothGrad, Integrated Gradients and GradCAM (Simonyan et al., 2014; Sundararajan et al., 2017; Selvaraju et al., 2017; Smilkov et al., 2017) are *gradient based local* explanations as they leverage gradients computed with respect to input dimensions of individual instances to explain model predictions. An alternate class of methods known as *global* explanations attempts to summarize the behavior of black box models as a whole (Bastani et al., 2017; Lakkaraju et al., 2019). In contrast, our work focuses on analyzing the disagreements between explanations generated by state-of-the-art methods.

Analyzing and Evaluating Post hoc Explanations. Prior research has studied several notions of explanation quality such as fidelity, stability, consistency and sparsity (Liu et al., 2021; Petsiuk et al., 2018; Slack et al., 2021; Zhou et al., 2021). Several metrics to quantify each of these aspects of explanation quality were also proposed (Zhou et al., 2021; Carvalho et al., 2019; Gilpin et al., 2018; Liu et al., 2021). As discussed in the introduction, most of these metrics are not general enough to cater to all models or real world settings. Follow up works leveraged these properties and metrics to theoretically and empirically analyze the behavior of popular post hoc explanations (Ghorbani et al., 2019; Slack et al., 2020; Dombrowski et al., 2019; Adebayo et al., 2018; Alvarez-Melis and Jaakkola, 2018; Levine et al., 2019; Chalasani et al., 2020; Agarwal et al., 2021). More specifically it has been shown that these explanations can be inconsistent or unstable (Ghorbani et al., 2019; Slack et al., 2020), prone to fair washing (Lakkaraju and Bastani, 2020; Slack et al., 2020; Aivodji et al., 2019), and can be unfaithful to the model to the extent that their usefulness can be severely compromised (Rudin, 2019). However, none of these works highlight or study the disagreement problem in explainable ML which is the focus of our work. The work that is closest to ours is the research by Neely et al. (2021) which demonstrates that certain post hoc explanation methods (e.g., LIME, Integrated Gradients, DeepLIFT, Grad-SHAP, DeepSHAP, and attention based explanations) disagree with each other based on rank correlation (Kendall's τ) metric. However, their work neither formalizes the notion of explanation disagreement by leveraging practitioner inputs, nor studies how explanation disagreements are resolved in practice which are the key contributions of this work.

Human Factors in Explainability. Many user studies evaluate how well humans can understand and utilize explanations (Doshi-Velez and Kim, 2017). Kaur et al. (2020) show that data scientists do not have a good understanding of the state-of-the-art interpretability techniques, and are unable to effectively leverage them in debugging ML models. Bhatt et al. (2020), conduct a survey to understand the use-cases for local explanations. Hong et al. (2020) conduct a similar survey to identify a variety of stakeholders across the model lifecycle, and highlight core goals: improving the model, making decisions, and building trust in the model. Furthermore, Lakkaraju and Bastani (2020) study if misleading explanations can fool domain experts into deploying racially biased models. Similarly, Poursabzi-Sangdeh et al. (2018) find that supposedly-interpretable models can lead to a decreased ability to detect and correct model mistakes. Lage et al. (2019) use insights from rigorous human-subject experiments to inform regularizers used in explanation algorithms. However, none of these works focus on understanding if and how often practitioners face explanation disagreement, and how they resolve it.

B. Interviews with Data Scientists

B.1. Participant demographics

We conducted 30-minute long semi-structured interviews with 25 data scientists who employ explainability techniques to understand model behavior and explain it to their customers and managers. All of these data scientists were employed in for-profit organizations, and worked for various companies in the technology and financial services sectors in the United States. Furthermore, all the participants used state-of-the-art (local) post hoc explanation methods such as LIME, SHAP, and gradient based methods in their day-to-day workflow. 19 of these participants (76%) were male, and 6 of them (24%) were female. 16 participants (64%)

had more than 2 years of experience working with explainability techniques, and the remaining 9 (36%) had about 8 to 12 months of experience.

C. Experimental Setup

C.1. Datasets

To carry out our empirical analysis, we leverage four well known datasets spanning three different data modalities (tabular, text, and images). For **tabular** data, we use the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) dataset (com, 2016) and the German Credit dataset (ger, 1994). This dataset comprises of seven features capturing information about the demographics, criminal history, and prison time of 4,937 defendants. Each defendant in the data is labeled either as high-risk or low-risk for recidivism based on the COMPAS algorithm's risk score. The German Credit dataset contains twenty features capturing the demographics, credit history, bank account balance, loan information, and employment information of 1,000 loan applicants. The class label is a loan applicant's credit risk (high or low). For **text** data, we use Antonio Gulli (AG)'s corpus of news articles (AG_News) (ag, 2004). The dataset contains 127,600 sentences (collected from 1,000,000+ articles from 2,000+ sources with a vocabulary size of 95,000+ words). The class label is the topic of the article from which a sentence was obtained (World, Sports, Business, or Science/Technology). For **image** data, we use the ImageNet$-1k$ (Russakovsky et al., 2015; ima, 2015) object recognition dataset. It contains 1,381,167 images belonging to 1000 object categories. We experiment with images from PASCAL VOC 2012 (voc, 2012) which provides segmentation maps that can be directly used as super-pixels for the explanation methods.

C.2. Black Box Models: Training and Performance

For tabular data, we train four models: a logistic regression model, a gradient-boosted tree model (50 estimators), a random forest model (50 estimators), and a densely-connected feed-forward neural network (with 4 hidden layers with relu activation consisting of 50, 100, 100, and 50 neurons, respectively). For the COMPAS dataset, we train the four models based on a 70%-30% train-test split of the dataset, using features to predict COMPAS risk score group. The test accuracies of the four models are 0.84, 0.83, 0.82, and 0.84, respectively. For the German credit dataset, we train the same four models based on a 80%-20% train-test split of the dataset, using features to predict credit risk group. The test accuracies of the four models are 0.74, 0.69, 0.75, and 0.70, respectively.

For text data, we trained a widely-used LSTM-based text classifier, based on 120,000 training samples and 7,600 test samples, to predict the news category of the article from which a sentence was obtained. The model performs with 90.67% accuracy. The architecture comprises of an embedding layer of dimension 300, followed by an LSTM layer of hidden size 256 connected to a four-dimensional output layer.

For image data, we use the pre-trained ResNet-18 model (He et al., 2016) and analyze explanations generated for predictions made to classify images to one of the 1000 classes. This model performs 69.758 % and 89.078 % on Accuracy@1 and Accuracy@5 metrics[3], respectively.

C.3. Explanation Methods

For tabular data, the perturbation-based explanation methods (LIME and KernelSHAP) were applied to explain all four models while the gradient-based explanation methods (Vanilla Gradients, Integrated Gradients, Gradient*Input, and SmoothGRAD) were applied to explain the logistic regression and neural network models to explain samples from the test set (1,482 samples for the COMPAS dataset and 200 samples for the German Credit dataset). Because gradients are not computed for tree-based models, the gradient-based explanation methods were not applied to the random forest and gradient-boosted tree models. When applying explanation methods with a sample size hyperparameter (LIME, KernelSHAP, Integrated Gradients, SmoothGRAD), we performed a convergence check and selected the sample size at which an increase in the number of samples does not significantly change the explanations. Change in explanations is measured by the L2 distance of feature attributions at the current versus previous sample size. For both COMPAS and German Credit datasets, we used the following number of perturbations/samples/steps for the following explanation methods: LIME (3,000), Integrated Gradients (1,500), SmoothGRAD (1,500). For the COMPAS dataset, when applying KernelSHAP, since the number of features is small, we used a sample size large enough to cover the entire coalition space ($2^7 = 128$ samples), thereby calculating exact Shapley values. For the German Credit dataset, when applying KernelSHAP, we used 3,000 samples, based on the convergence analysis.

For text data, we applied all six explanation methods on the LSTM-based classifier to explain predictions for 7,600 samples in the test set. For LIME and KernelSHAP, we follow the convergence analysis described above and find that attributions do not change significantly beyond 500 perturbations; hence, we use 500 perturbations for LIME and KernelSHAP. Integrated Gradients explanations were generated using 500 steps which is higher than the recommended number of steps mentioned in (Sundararajan et al., 2017). SmoothGRAD explanations were generated using 500 samples to get the most confident attribution which is significantly higher the recommended number of 50 samples (Smilkov et al., 2017).

[3] https://pytorch.org/vision/stable/models.html

For image data, we applied all six explanation methods on the ResNet-18 model (He et al., 2016) to explain predictions for the PASCAL VOC 2012 test set of 1,449 samples. Integrated Gradients explanations were generated using 400 steps, significantly higher than the recommendation of 300 (Sundararajan et al., 2017), to obtain a stable and confident attribution map. Similarly, SmoothGRAD explanations were generated using a sample size of 200 which is also higher than the recommended sample size of 50 (Smilkov et al., 2017). For LIME and KernelSHAP, we chose 100 perturbations to train the surrogate model as we did not notice any significant changes in attributions beyond 50 perturbations. KernelSHAP and LIME were used to compute attributions of super-pixels annotated in PASCAL VOC 2012 segmentation maps. Due to a larger feature space in images compared to the previous tabular and text datasets, disagreement metrics based on top-k features may not provide a clear picture. Hence, we use Rank Correlation and cosine distance between attribution maps generated by a pair of explanation methods as the disagreement metric. Higher cosine distance between attribution maps indicate larger disagreement between explanation methods.

C.4. Applying metrics to evaluate explanations

For tabular and text data, we apply rank correlation and pairwise rank agreement across all features; and feature agreement, rank agreement, sign agreement, signed rank agreement across top-k features for varying values of k. For image data, metrics that operate on the top-k features are more applicable to super-pixels. Thus, we apply the six disagreement metrics on explanations output by LIME and KernelSHAP (which leverage super pixels), and calculate rank correlation (across all pixels as features) between the explanations output by gradient-based methods. See Appendix C for details.

D. Results from Empirical Analysis of Disagreement Problem

D.1. COMPAS Dataset

D.1.1. Figure description: metrics measuring agreement among a set of selected features

Disagreement between explanation methods as measured by rank correlation (left column) and pairwise rank agreement (right column) over test set data points. Both metrics are calculated across all features. Heatmaps show the average metric value and boxplots show the distribution of metric values for each pair of explanation methods. In heatmaps, lighter colors indicate stronger disagreement. Minimum and maximum standard errors are indicated below each heatmap.

D.1.2. Figure description: metrics measuring agreement among top-k features

Disagreement between explanation methods as measured by rank agreement, feature agreement, sign agreement, and signed rank agreement (each row is one metric). By definition, when k equals the full set of features, feature agreement equals one. Heatmaps show the average metric value for each pair of explanation methods, with lighter colors indicating stronger disagreement. Minimum and maximum standard errors are indicated below each heatmap.

D.2. ImageNet Dataset

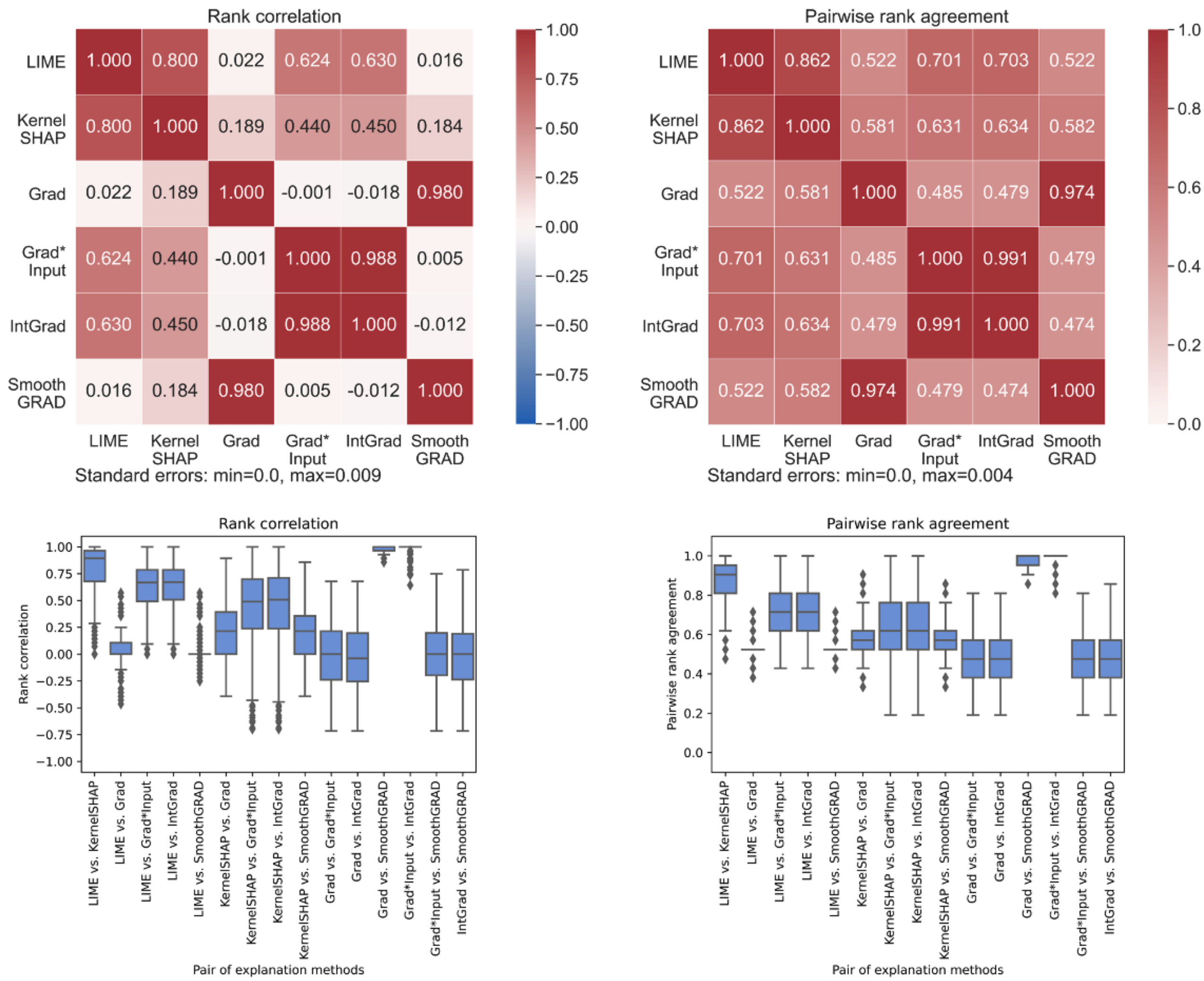


Figure 3: Disagreement between explanation methods for neural network model trained on COMPAS dataset. Figure description in Appendix D.1.1.

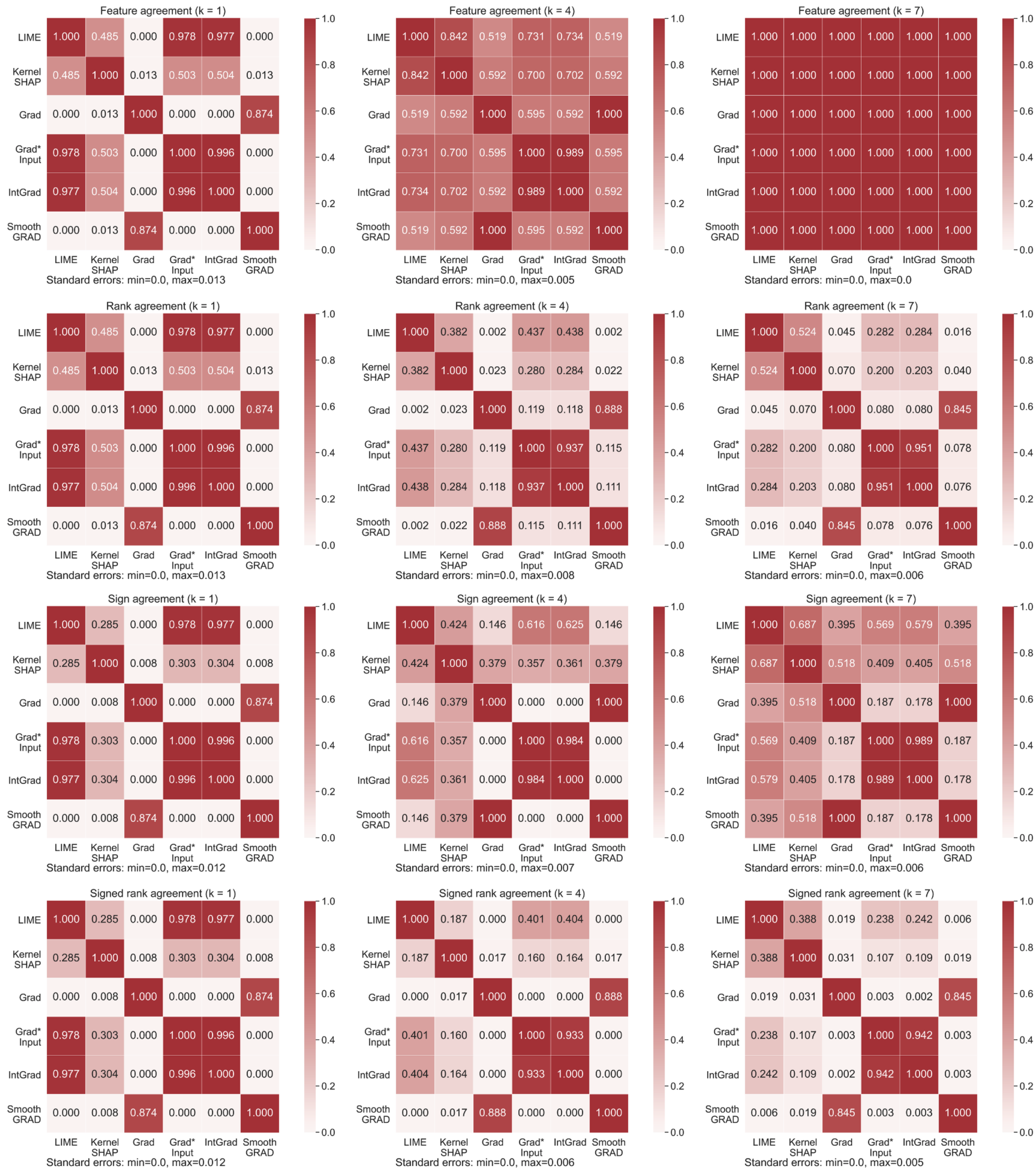


Figure 4: Disagreement between explanation methods for neural network model trained on COMPAS dataset. Figure description in Appendix D.1.2.

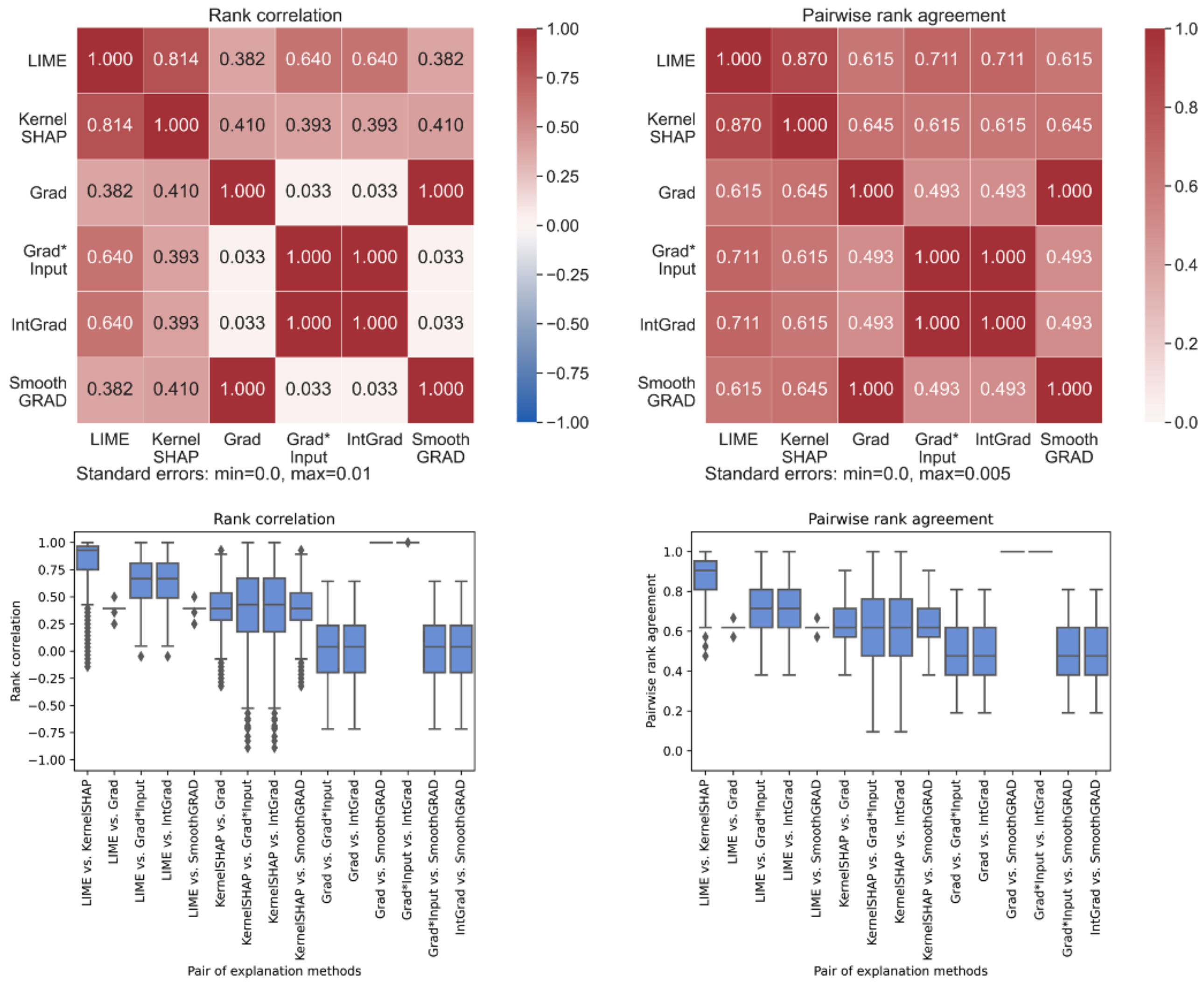


Figure 5: Disagreement between explanation methods for logistic regression model trained on COMPAS dataset. Figure description in Appendix D.1.1.

Metrics	**ResNet-18**
Rank correlation	0.8977
Pairwise rank agreement	0.9302
Feature agreement	0.9535
Rank agreement	0.8478
Sign agreement	0.9218
Signed rank agreement	0.8193

Table 2: Disagreement on ImageNet between LIME and KernelSHAP

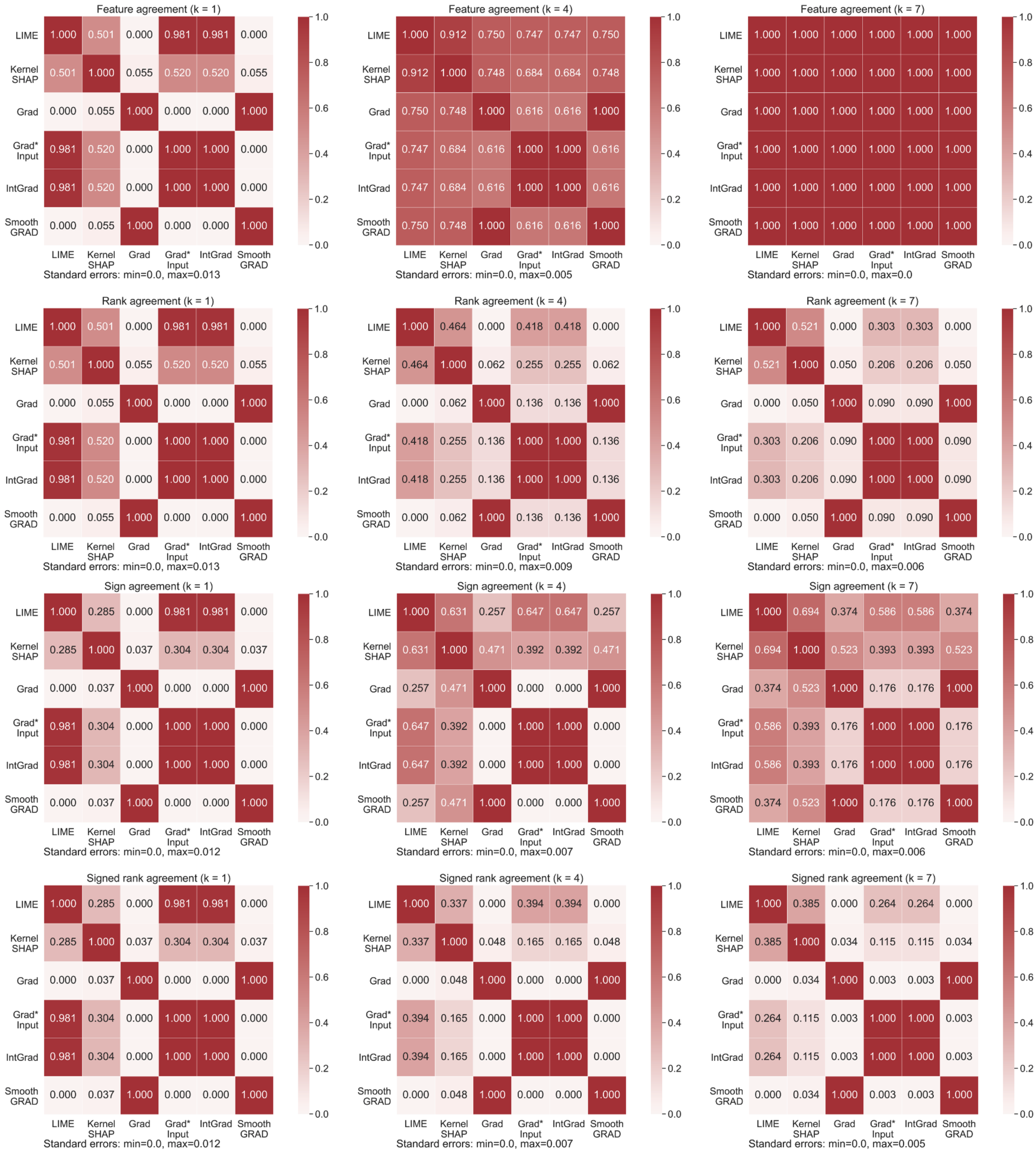


Figure 6: Disagreement between explanation methods for logistic regression model trained on COMPAS dataset. Figure description in Appendix D.1.2.

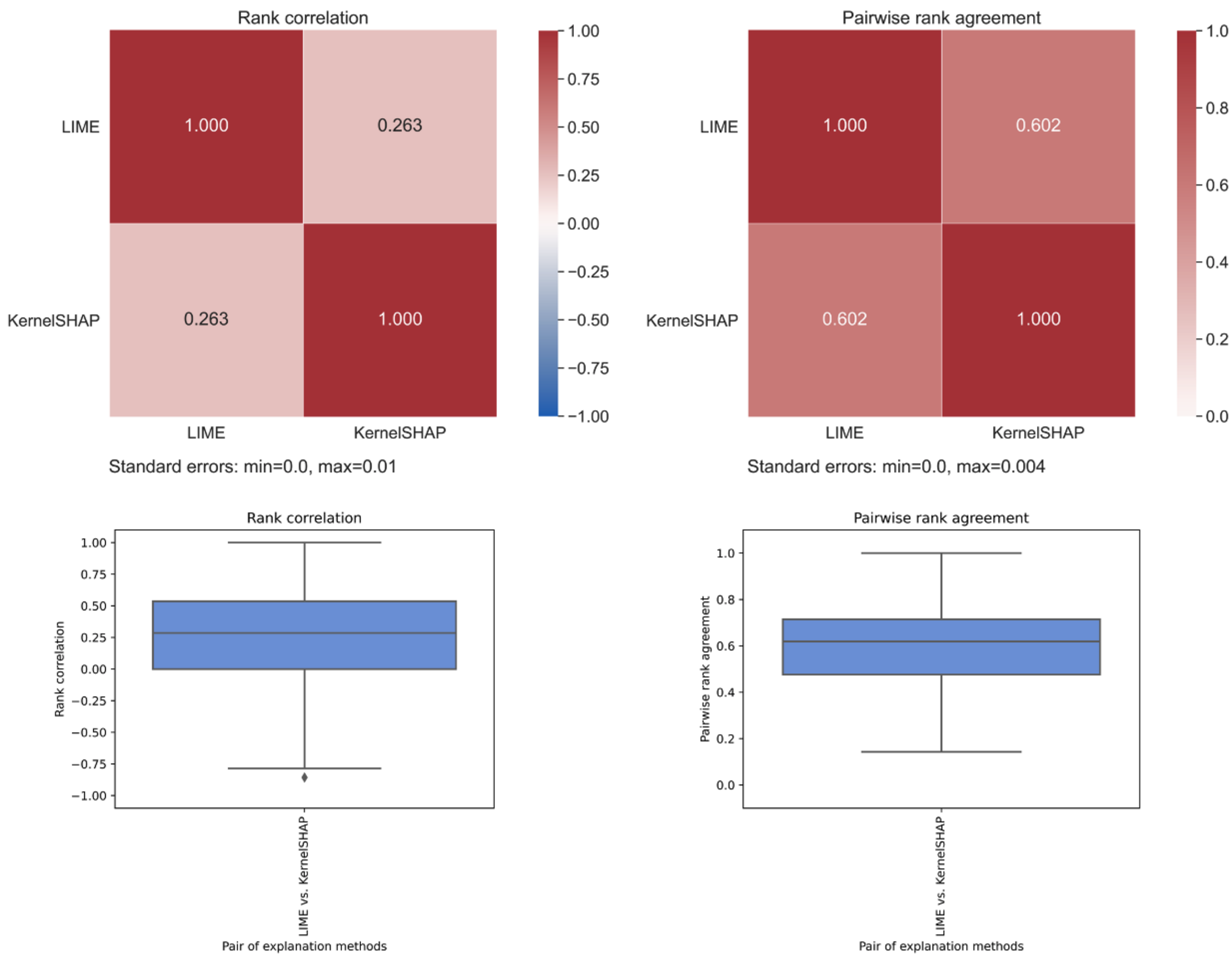


Figure 7: Disagreement between explanation methods for random forest model trained on COMPAS dataset. Figure description in Appendix D.1.1.

Figure 8: Disagreement between explanation methods for random forest model trained on COMPAS dataset. Figure description in Appendix D.1.2.

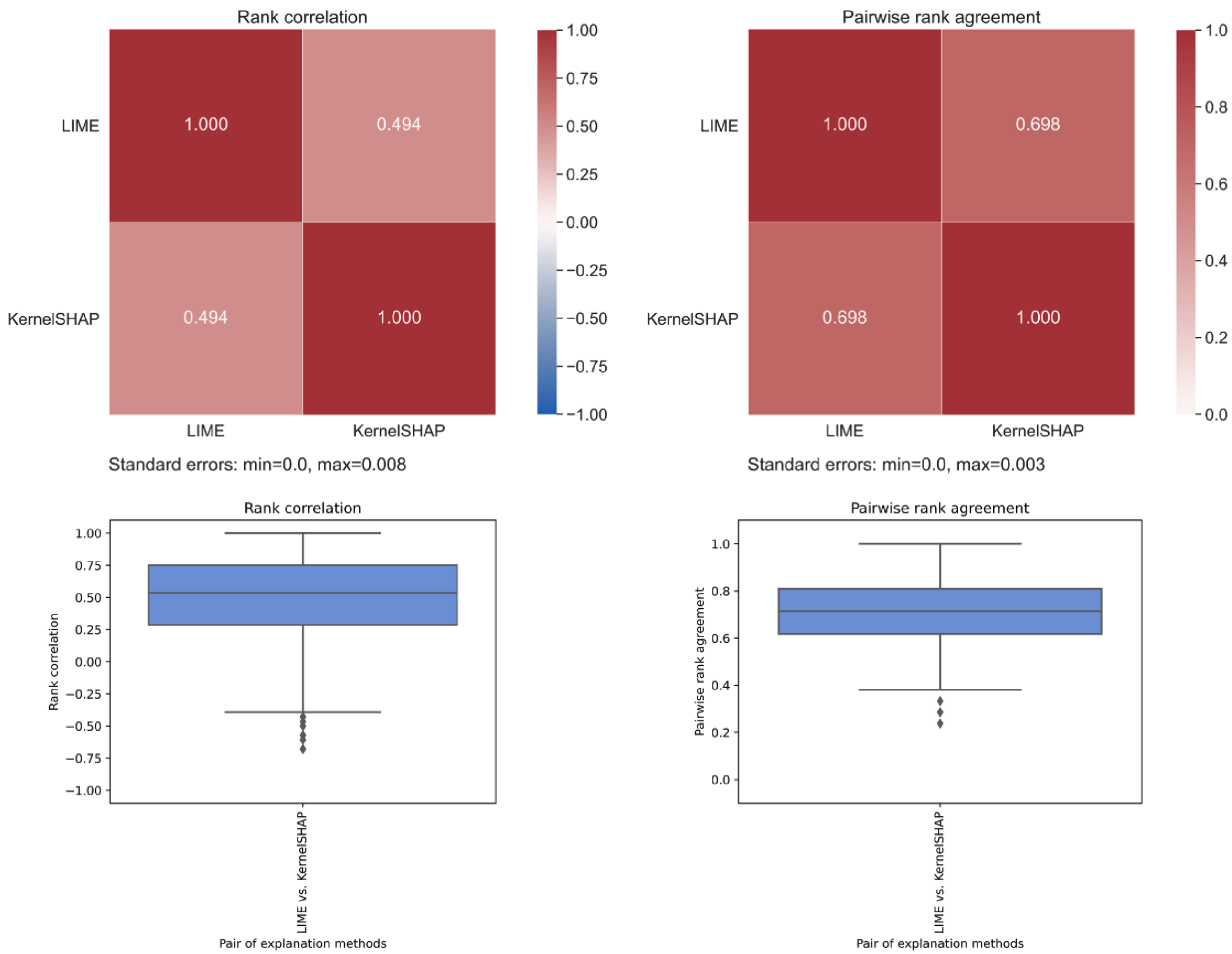


Figure 9: Disagreement between explanation methods for gradient-boosted tree model trained on COMPAS dataset. Figure description in Appendix D.1.1.

Figure 10: Disagreement between explanation methods for gradient-boosted tree model trained on COMPAS dataset. Figure description in Appendix D.1.2.

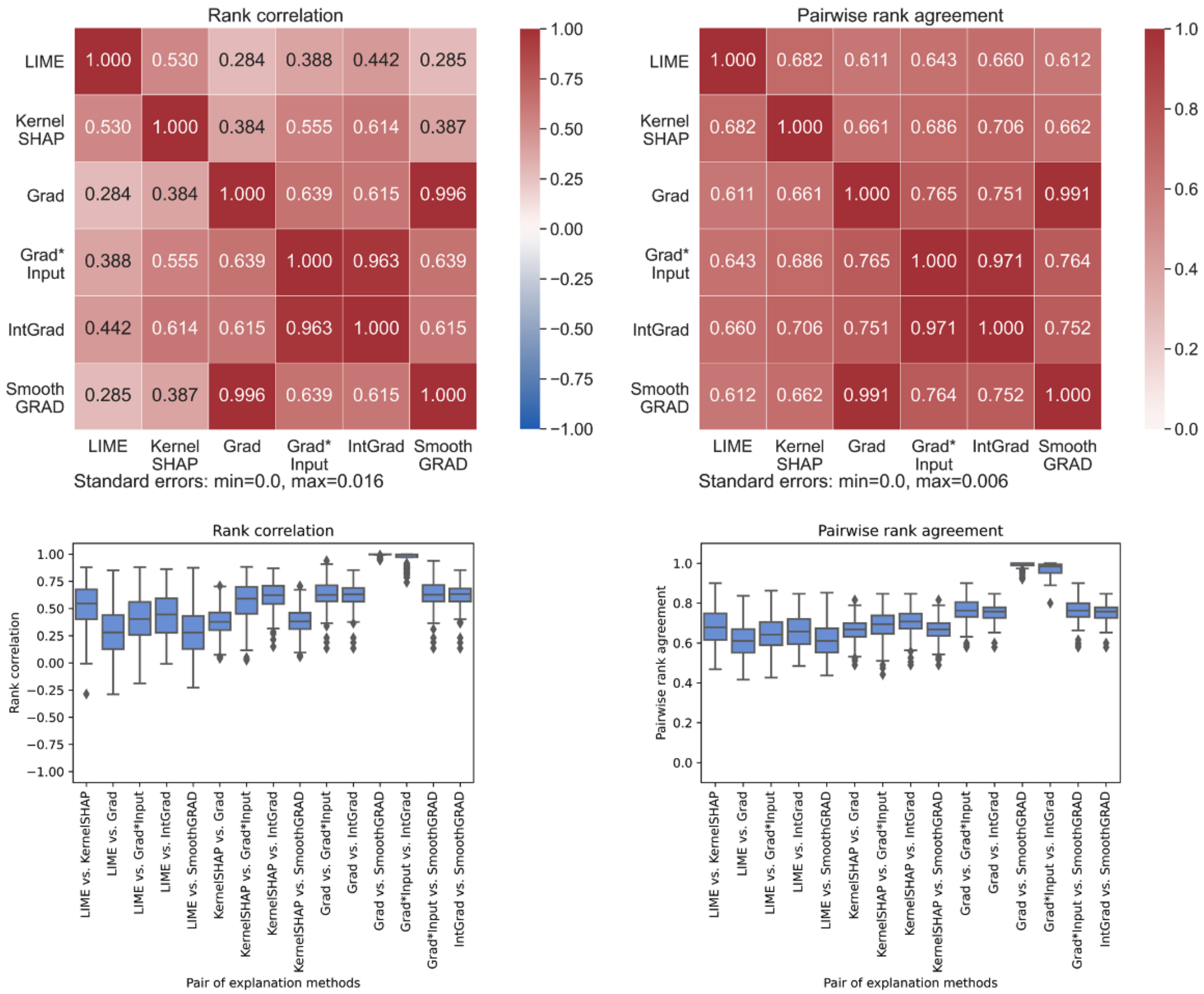


Figure 11: Disagreement between explanation methods for neural network model trained on German Credit dataset. Figure description in Appendix D.1.1.

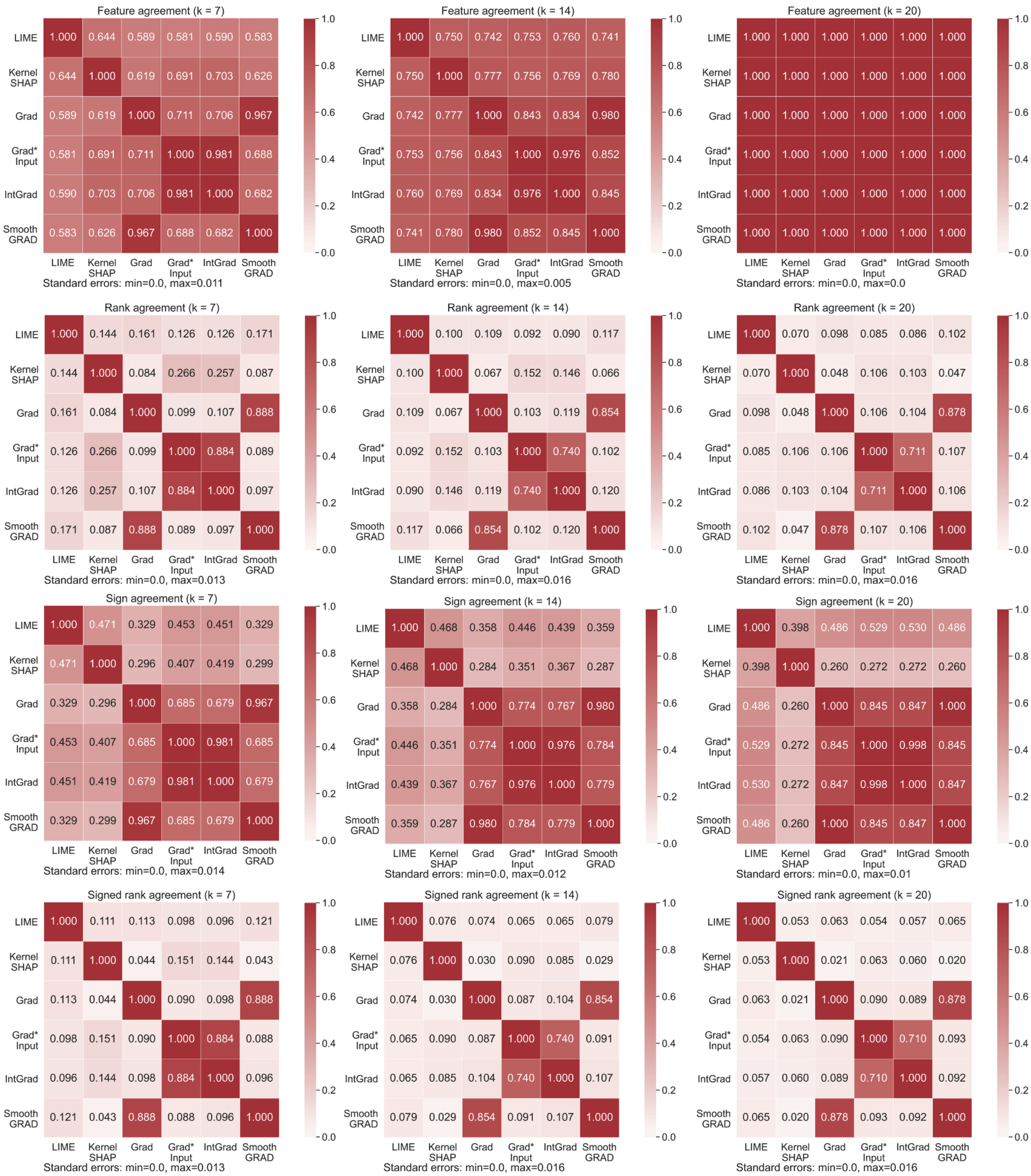


Figure 12: Disagreement between explanation methods for neural network model trained on German Credit dataset. Figure description in Appendix D.1.2.

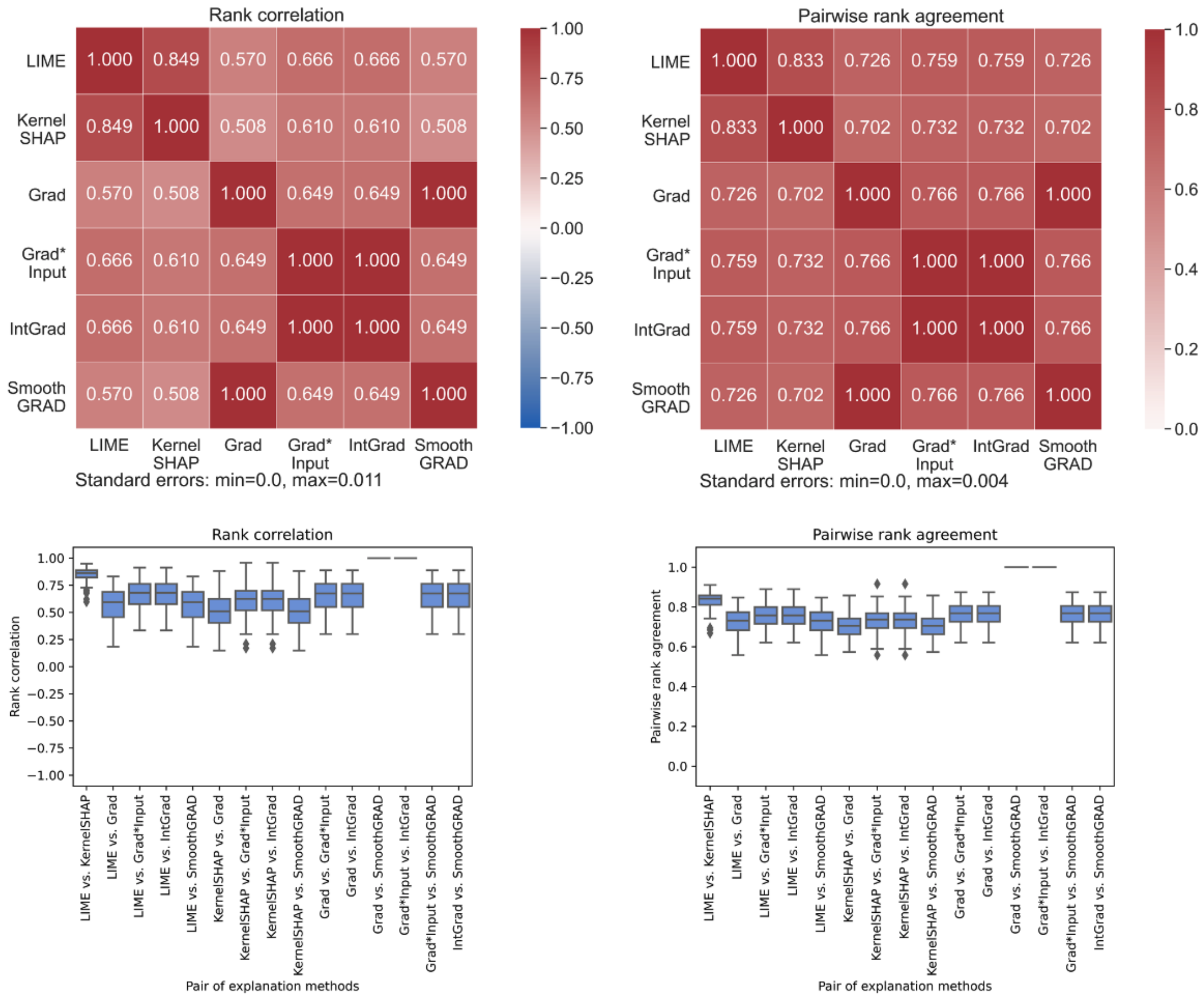


Figure 13: Disagreement between explanation methods for logistic regression model trained on German Credit dataset. Figure description in Appendix D.1.1.

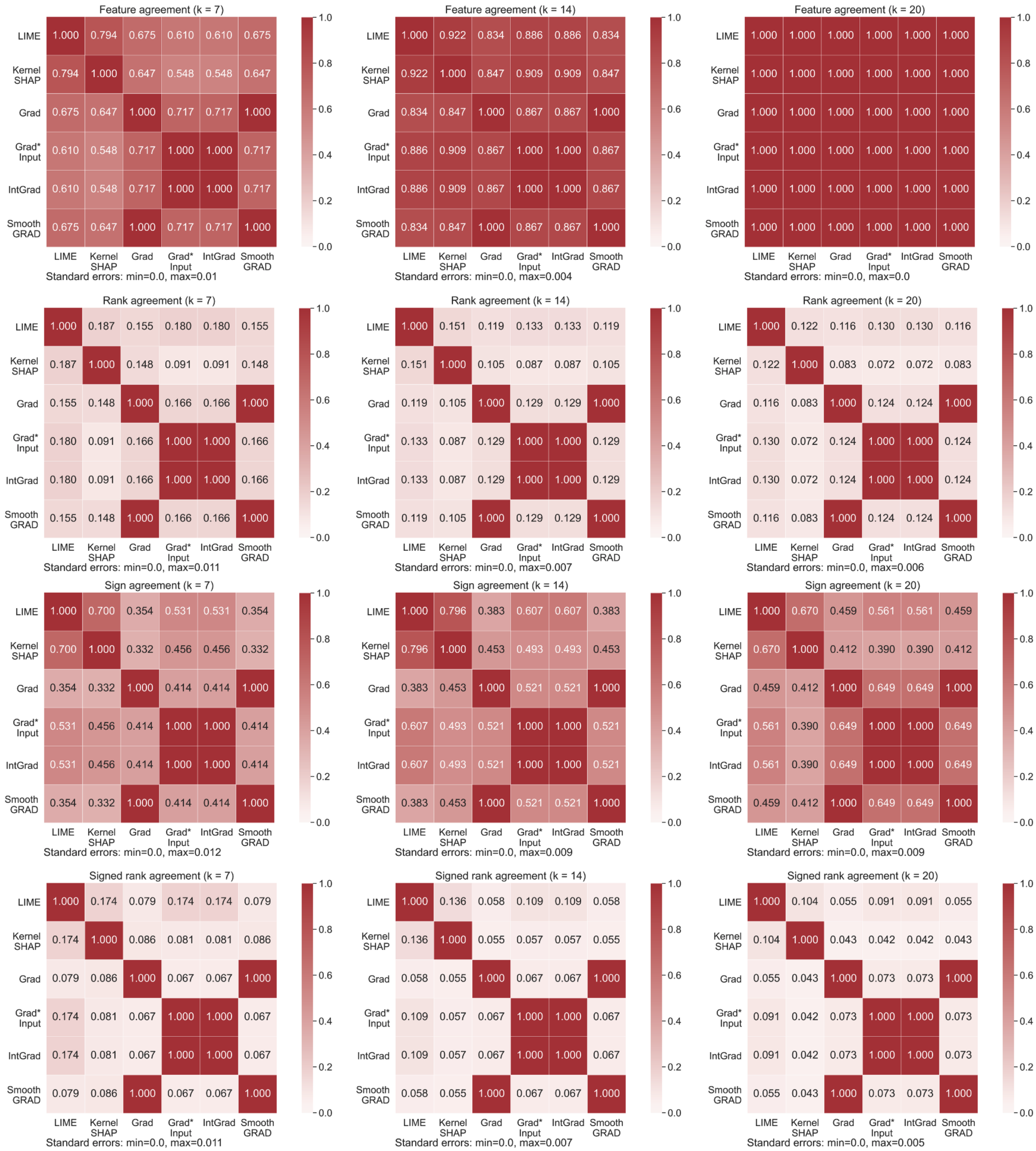


Figure 14: Disagreement between explanation methods for logistic regression model trained on German Credit dataset. Figure description in Appendix D.1.2.

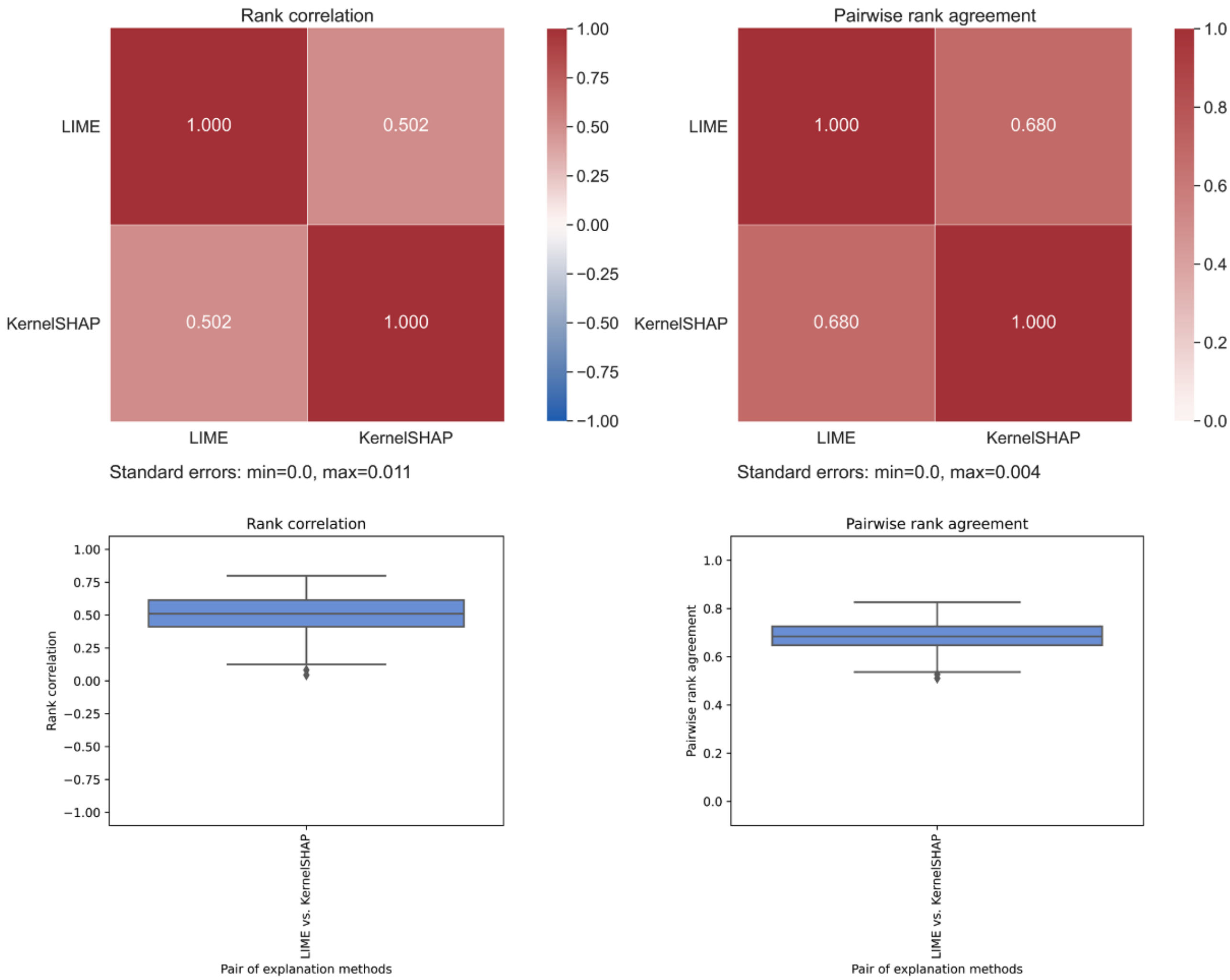


Figure 15: Disagreement between explanation methods for random forest model trained on German Credit dataset. Figure description in Appendix D.1.1.

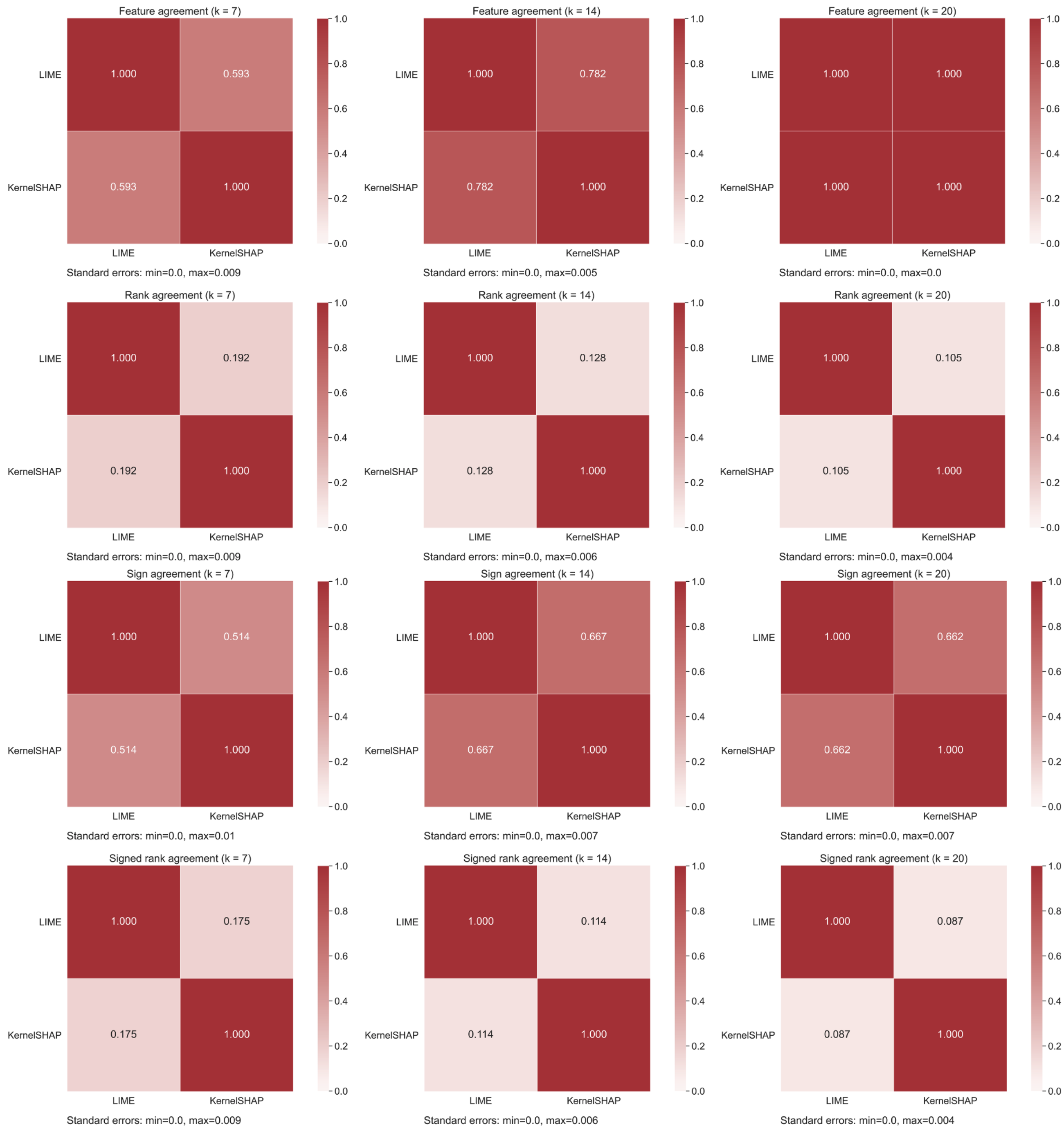


Figure 16: Disagreement between explanation methods for random forest model trained on German Credit dataset. Figure description in Appendix D.1.2.

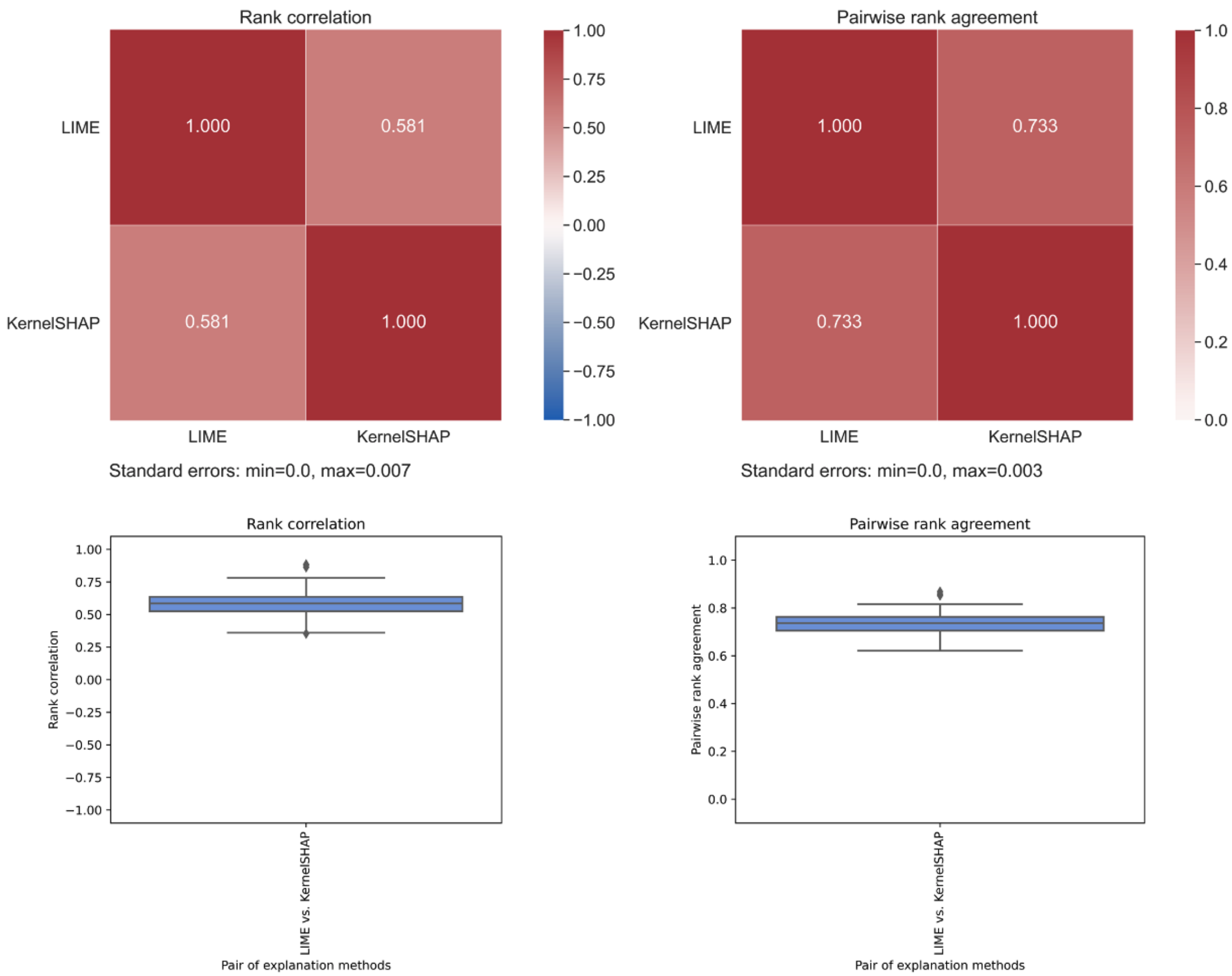


Figure 17: Disagreement between explanation methods for gradient-boosted tree model trained on German Credit dataset. Figure description in Appendix D.1.1.

Figure 18: Disagreement between explanation methods for gradient-boosted tree model trained on German Credit dataset. Figure description in Appendix D.1.2.

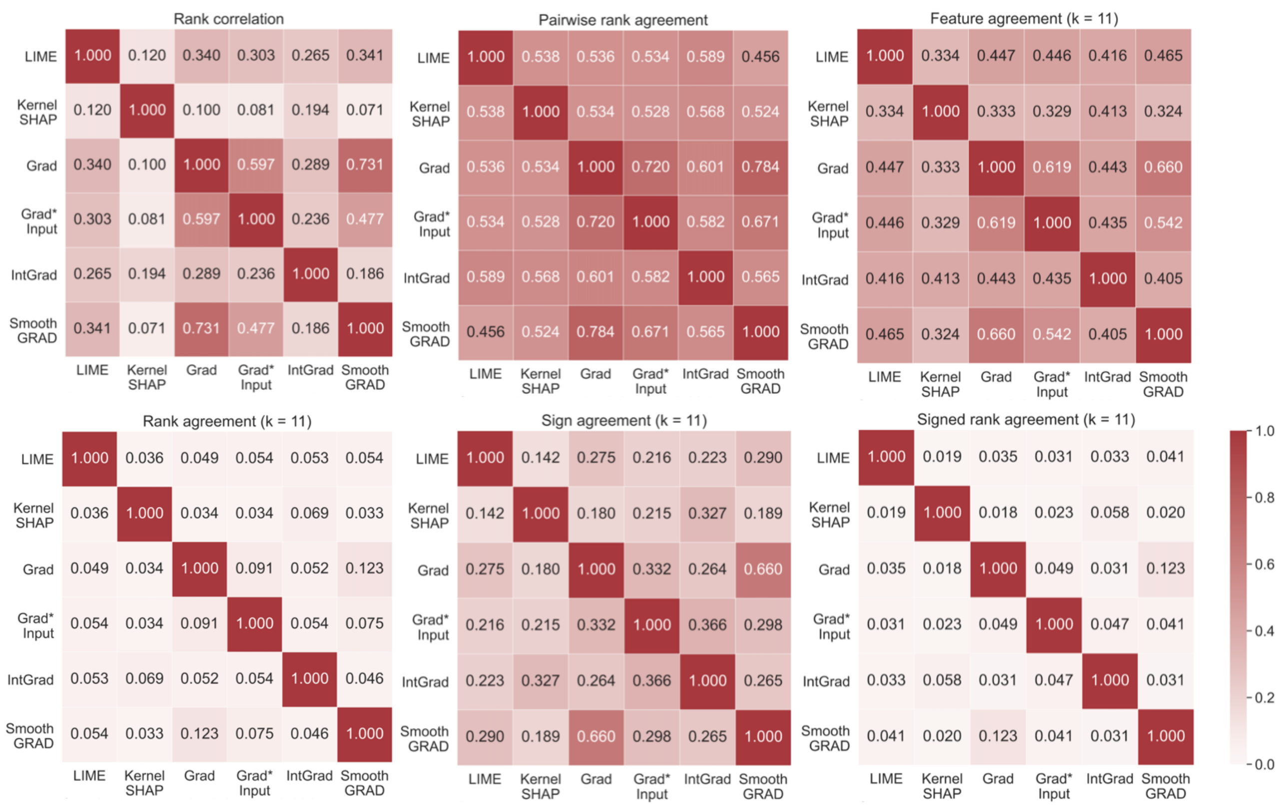


Figure 19: Disagreement between explanation methods for the LSTM model trained on the AG_News dataset using $k = 11$ features for metrics operating on top-k features, and all features for other metrics. Each heatmap shows the metric value averaged over test data for each pair of explanation methods. Lighter colors indicate more disagreement. Standard error ranges from 0.0 to 0.0025 for all six metrics.

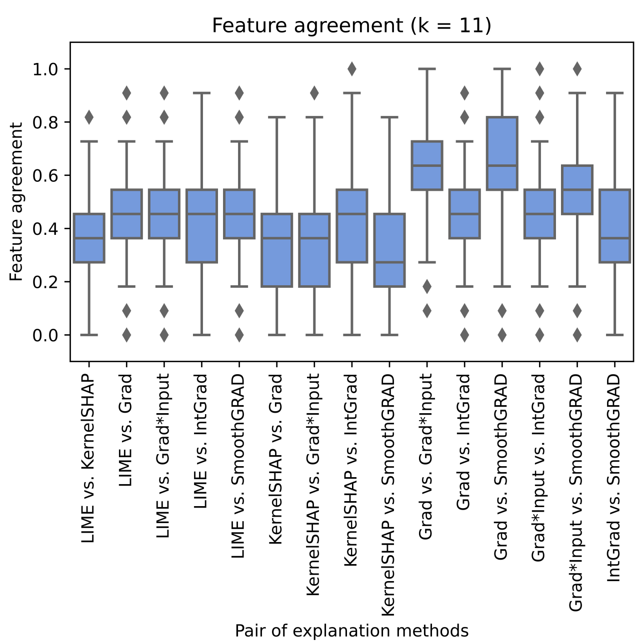


Figure 20: Box plot for feature agreement on AG_News dataset

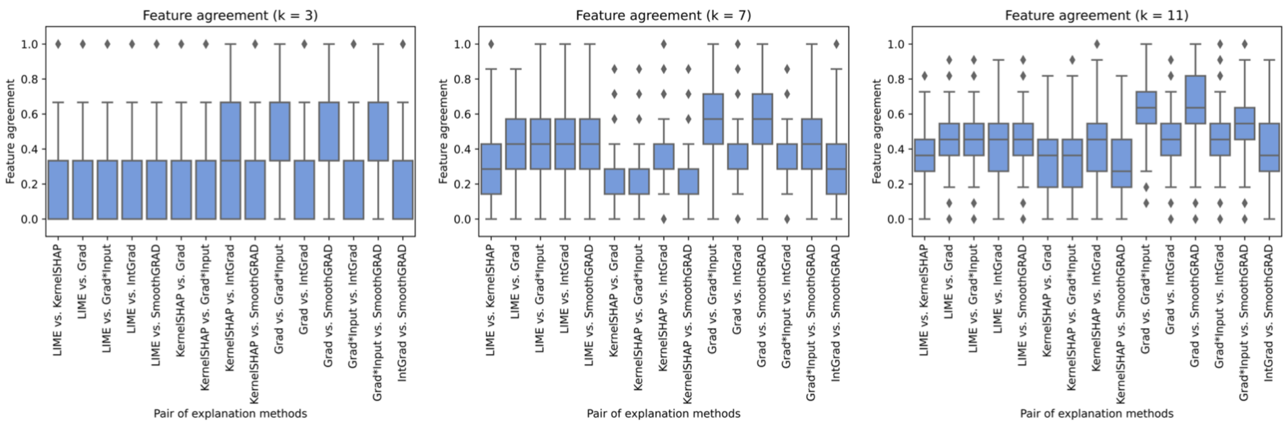


Figure 21: Box plot for feature agreement on AG_News dataset for k = [3,7,11]

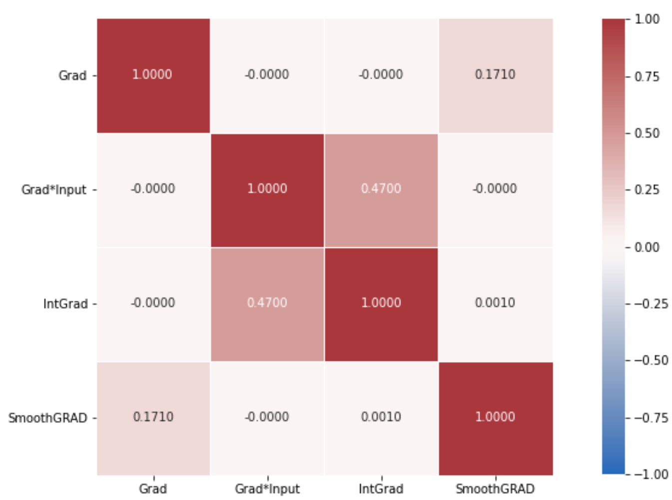


Figure 22: Rank correlation for explanations computed at pixel level by gradient-based explanation methods

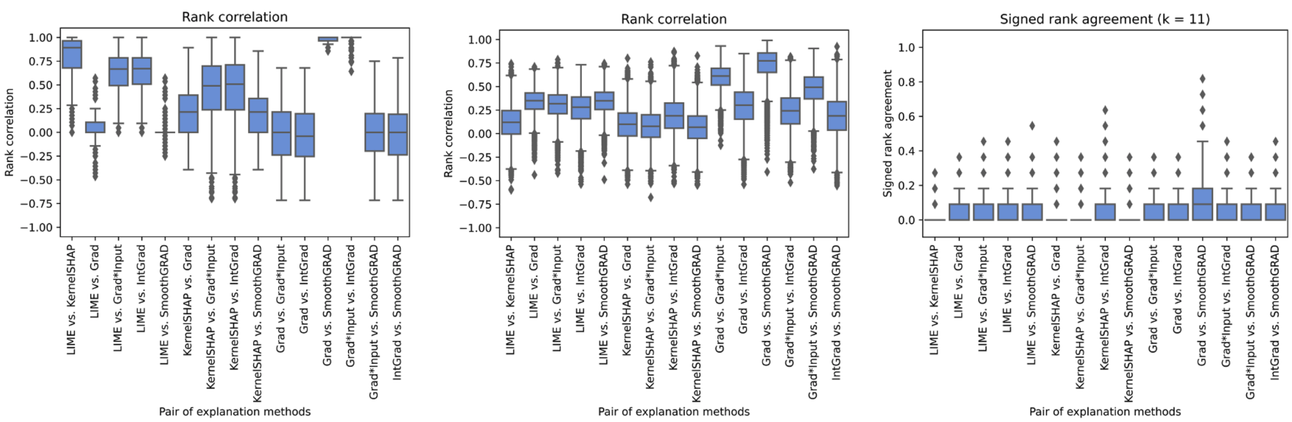


Figure 23: Distribution of rank correlation over all features for neural network model trained on COMPAS (left), and rank correlation across all features (middle) and signed rank agreement across top-11 features (right) for neural network model trained on AG_News.

D.3. Results description

D.3.1. TEXT DATA

For text data, we deal with a high-dimensional feature space where words are features. For $k = 11$ (25% of the average sentence length), we observe severe disagreements across all the six disagreement metrics (Appendix Figure 19). Rank agreement and signed rank agreement are the lowest between explanations with values under 0.1 for most cases indicating disagreement in over 90% of the top-k features. Trends are quite similar for rank correlation and feature agreement with better agreement between gradient-based explanation methods.

We also notice specific patterns of agreement between a group of explanation methods. For example, there is a high rank correlation between gradient-based explanations. (Figure 23, middle and right). Disagreement is also lower between LIME and other explanation methods compared to KernelSHAP and other methods (Figure 23, middle and right; Appendix D). In addition, there is stronger disagreement among explanation methods for text compared to tabular data, suggesting that disagreement may worsen as the number of features increases.

D.3.2. IMAGE DATA

Unlike earlier trends with tabular and text data, we see higher agreement between KernelSHAP and LIME on all the six metrics: rank correlation of 0.8977, pairwise rank agreement of 0.9302, feature agreement of 0.9535, rank agreement of 0.8478, sign agreement of 0.9218 and signed rank agreement of 0.8193. However, the trends are quite opposite when we compute rank correlation at pixel-level for gradient-based methods (Appendix D.2). For instance, rank correlation between Integrated Gradients and SmoothGrad is 0.001, indicating high disagreement. The disagreement is similarly quite high in case of other pairs of gradient based methods. This suggests that disagreement may vary significantly based on the granularity of image representation.

E. Omitted Details from Section 4

E.1. Screenshots of UI

In Figures 24 and 25, we present screenshots of the UI that participants are presented with before beginning the study. The purpose of this introduction page is to familiarize the participants with the COMPAS prediction setting, the six explainability methods we use, and the explainability plots we show in each of the prompts.

E.2. Prompts Used

In this section, we share the 15 prompts that we showed users. Each prompt highlights a pair of different explainability algorithms on a COMPAS data point. For each pair, we chose the data point from the entire COMPAS set that maximized the rank correlation between the explanations.

E.3. User Study Questions

In each of the five prompts, we asked participants the following questions, which we refer to as *Set 1*. Questions 3-4 were only shown if the user selected *Mostly agree*, *Mostly disagree*, or *Completely disagree* to Question (1).

1. To what extent do you think the two explanations shown above agree or disagree with each other? (choice between *Completely agree, Mostly agree, Mostly disagree, Completely disagree*)
2. Please explain why you chose the above answer.
3. Since you believe that the above explanations disagree (to some extent), which explanation would you rely on? (choice between *Algorithm 1 explanation, Algorithm 2 explanation, It depends*)
4. Please explain why you chose the above answer.

After answering all five prompts, the user was then asked the following set of questions, which we refer to as *Set 2*. Questions 4-9 were only shown if the user selected *Yes* to Question 3.

1. (Optional) What is your name?
2. What is your occupation? (eg: PhD student, software engineer, etc.)
3. Have you used explainability methods in your work before? (*Yes/No*)
4. What do you use explainability methods for?
5. Which data modalities do you run explainability algorithms on in your day to day workflow? (eg: tabular data, images, language, audio, etc.)
6. Which explainability methods do you use in your day to day workflow? (eg: LIME, KernelSHAP, SmoothGrad, etc.)
7. Which methods do you prefer, and why?
8. Do you observe disagreements between explanations output by state of the art methods in your day to day workflow?
9. How do you resolve such disagreements in your day to day workflow?

E.4. Further analysis of overall agreement levels

In this section, we present further plots analyzing responses to questions (1) in Set 1. As shown in Figure 28(a), only 32% of responses were *Mostly Agree/Completely Agree* and 68% were *Mostly Disagree/Completely Disagree*, indicating that participants experienced the disagreement problem. We also grouped the responses by prompt, shown in Figure 28(b), highlighting that different pairs of algorithms can have different levels of disagreement. We removed prompts with less than 4 total responses. We see that there are varying levels of disagreements among prompts. For example, all participants who were shown the Gradient vs. SmoothGrad prompt believed they agreed to some extent, while all participants who were shown the Gradient vs. Integrated Gradients prompt believed they disagreed to some extent.

E.5. Further analysis of reasons participants chose specific algorithms

In this section, we analyze the responses to Set 1, Question (3) in Section E.3. We saw, in 4.2.2, that algorithms such as KernelSHAP were favored over other algorithms. In Table 3, we list the top reasons the four most frequently chosen algorithms were preferred, showcasing direct quotes from participants.

E.6. Analysis of reasons participants chose neither algorithm

In this section, we analyze the responses to Set 1, Question (4) in Section E.3, focusing on when participants selected *"It depends"* in Question (3), which was chosen in 38% of cases. Again, we present an overarching summary of the reasons participants made this decision in Table 4.

E.7. Further analysis of concluding questionnaire

In this section, we extend the analysis presented in 4.2.3, analyzing the responses to questions in Set 2 of Section E.3. As stated in 4.2.3, we received a total of 20 positive responses to Question (3), but one declined to answer Questions (4) through (9). Therefore, we analyze the remaining 19 responses.

Introduction

COMPAS is a popular commercial algorithm used by judges for determining a criminal defendant's likelihood of reoffending (recidivism).

The COMPAS dataset consists of 7 features:

- **age**
- **two_year_recid**: whether the defendant recidivated within 2 years of the original crime
- **priors_count**: number of prior crimes committed
- **length_of_stay**: length the defendant stayed in jail
- **c_charge_degree**: one of Misdemeanor, Felony
- **sex**: one of Male, Female
- **race**: one of African-American, Asian, Caucasian, Hispanic, Native American, or Other

For this study, we trained a neural network on the COMPAS dataset to **predict a criminal defendant's COMPAS risk score (low or high), corresponding to whether he/she would commit a crime after two years past the date of the original crime**. Since it is important to understand our model's predictions (explainability), we also ran six popular explainability algorithms on various input points.

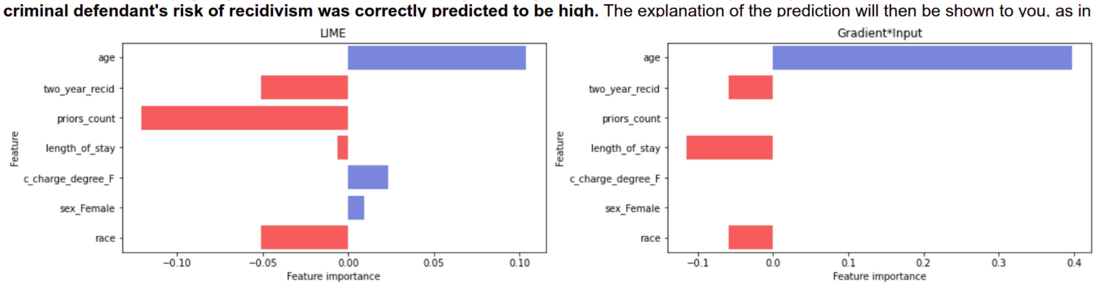
The explainability algorithms we use are listed here. **You do not need to understand them past what we have described here.**

- **LIME**: an explanation based on a locally linear approximation of the model at that input
- **KernelSHAP**: a combination of LIME and Shapley Values, which identify the contribution of each feature based on interactions with other features
- **Gradient**: the gradient of the model at the input
- **Gradient*Input**: the dot product of the input features and the gradient explanation
- **SmoothGrad**: weighted average of the gradient at points around the input
- **Integrated Gradients**: a modification of the gradient method to satisfy two axioms, *sensitivity* and *implementation invariance*

Figure 24: This is a screenshot of the first half of the introductory page, describing our COMPAS risk score prediction setting and briefly summarizing the six explainability algorithms used (with links to their corresponding papers for the interested participant).

Your Task

On each of the next 5 pages, you will see the result of two explainability methods on the same input sample from COMPAS, as shown below. **Assume that the criminal defendant's risk of recidivism was correctly predicted to be high.** The explanation of the prediction will then be shown to you, as in the figure below.



The y-axis lists each of the 7 COMPAS features, and the x-axis shows the importance of that feature. Positive importance values are shown in blue, while negative importance values are shown in red. A **high positive importance** for a feature means that the feature contributed greatly to the correct prediction, while a **high negative importance** means that the feature negatively contributed (was misleading) to the prediction. Note the different x-axis scales resulting from different methods. You will be asked to compare the two explanations.

Figure 25: This is a screenshot of the second half of the introductory page, describing the concrete task and an explanation of what is shown in the explainability plots.

Table 3: Reasons participants chose the top four most favored explainability algorithms (KernelSHAP, SmoothGrad, LIME, and Integrated Gradients) over others when explanations disagreed.

Algorithm	Reasons that algorithm was chosen in disagreement
KernelSHAP	• [36%] SHAP is better for tabular data (*"SHAP is more commonly used [than Gradient] for tabular data"*) • [25%] SHAP is more familiar (*"More information present + more familiarity"*) • [14%] SHAP is a better algorithm overall (*"SHAP seems more methodical than LIME"*, *"SHAP is a more rigorous approach [than LIME] in theory"*)
SmoothGrad	• [33%] SmoothGrad paper is newer or better (*"SmoothGrad is apparently more robust", "SmoothGrad is often considered improved verison of grad"*) • [58%] Reasons based on the explainability map shown (*"directionality of the attributions ... [agree] with intuition"*, *"gradient has unstability problems [, so] smoothgrad"*)
LIME	• [54%] LIME is better for tabular data (*"I use LIME for structured data."*) • [15%] LIME is more familiar/easier to interpret (*"I am more familiar with LIME"*, *"LIME is easy to interpret"*)
Integrated Gradients	• [86%] Integrated Gradients paper is better (*"IG came after gradients and paper shows improvements"*, *"integrated gradients paper showed improvements [over Gradient $\times$ Input]"*

Table 4: Reasons people answered *"It depends"* after being asked to choose between disagreements

Rationale	Representative Quote
1. Need more information	• *"need to see the final prediction of the model and the feature values"*
2. Pick neither explanation	• *"No compelling reason to choose one over the other. Both don't align with intuition."*
3. Unsure/Don't know	• *"I'm not sure which of the two methods is more trustworthy"*
4. Would consult an expert	• *"I would ask a domain expert for his/her opinion"*
5. Combine explanations	• *"I would combine both – note that age might be doing weird things, but that length of stay and race both contribute to a negative prediction"*
6. Depends on use case	• *"The two methods have different interpretations - it depends on if I'm more interested in comparing my explanation to some baseline individual state versus just interested in understanding the immediate local behavior"*

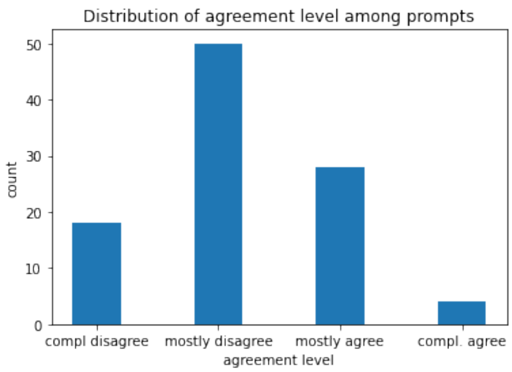
Figure 26: The user interface for a prompt. The user is shown two explanations for a COMPAS data point, showing the feature importance value of each of the 7 features. Red and blue indicate negative and positive feature values, respectively. See the text for more details.

In Question (4), we found that study participants use explainability methods for a variety of reasons such as understanding models, debugging models, help explain models to clients, research. In Question (5), we found that 16 of 19 participants employed explanations for tabular data, 6 of 19 participants for text and language data, 11 of 19 participants for image data, and 1 of 19 for audio data. In Question (6), we found that 14 of 19 participants used LIME, 14 of 19 participants used SHAP, and 13 of 19 participants used some sort of gradient-based methods. Participants also indicated using methods like GradCAM, dimensionality reduction, MAPLE, and rule-based methods. In Question (7), 9 of 19 participants stated that they preferred both LIME and SHAP, with another 3 of 19 participants stating LIME only. We showcase some intriguing answers from Question (7) below:

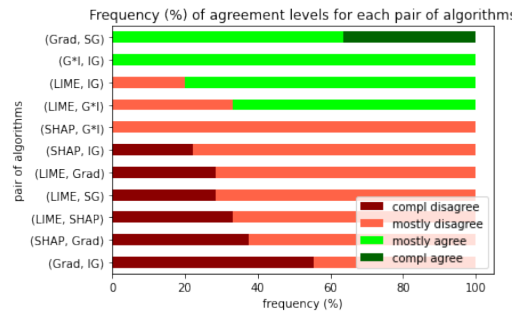
- “LIME and SHAP seem to be the most universally applicable and I can understand.”
- “Methods with underlying theoretical justifications such as KernelSHAP and Integrated Gradients”
- “lime and shap ... [easy to implement] and can work with black box”
- “shap and lime because ... [they are] easy to understand and have standard implementations”
- “LIME, because everything else isn’t necessarily capturing what I actually want to know about the local behavior”

Finally, we provide additional quotes highlighting the responses to Questions (8) and (9), which were briefly analyzed in Section 4.2.3. These are shown in Table 5.

Figure 27: Images showing the 15 prompts we used. Each prompt shows the explanation of the same input point with two different interpretability algorithms.



((a)) This figure shows the distribution of responses in aggregation over all prompts. The x-axis shows the four possible responses, and the y-axis shows the number of times that response was chosen. Observe that in 68% of cases, participants indicated that the prompts mostly or completely disagreed.



((b)) This figure shows the distribution of responses, sorted by prompt. The y-axis shows the pair of explainability algorithms shown in the prompt, and the x-axis shows the frequency that each response was chosen.

Figure 28: These figures show the distribution of answers to Question (1) in Set (1) from Section E.4 in aggregation over all participants.

Table 5: Representative quotes highlighting themes of how participants address the disagreement problem in their day to day work

Category of Response	Samples Quotes
1. Make arbitrary decisions (50%).	• *"Such disagreements are resolved by data scientists picking their favorite algorithm"* • *"I try to use rules of thumb based on results in research papers and/or easy to understand outputs."* • *"I favor lime and shap because there is well documented packages on github"*
2. Unsure/Don't know/Don't resolve (36%)	• *"there is no clear answer to me. I hope research community can provide some guidance"* • *"unfortunately there is no good answer at my end ... I hope you can help me with finding an answer"*
3. Use other metrics (fidelity) (14%).	• *"By quantitative assessment of feature importance methods that assess specific properties like faithfulness"* • *"I might try and use some metric to measure fidelity."*