Evaluating Explanations: How much do explanations from the teacher aid students?

Danish Pruthi^{1*} Bhuwan Dhingra² Livio Baldini Soares² Michael Collins² Zachary C. Lipton¹ Graham Neubig¹ William W. Cohen²

¹ Carnegie Mellon University ² Google Research

{ddanish, zlipton, gneubig}@cs.cmu.edu {bdhingra, liviobs, mjcollins, wcohen}@google.com

Abstract

While many methods purport to explain predictions by highlighting salient features, what precise aims these explanations serve and how to evaluate their utility are often unstated. In this work, we formalize the value of explanations using a student-teacher paradigm that measures the extent to which explanations improve student models in learning to simulate the teacher model on unseen examples for which explanations are unavailable. Student models incorporate explanations in training (but not prediction) procedures. Unlike many prior proposals to evaluate explanations, our approach cannot be easily gamed, enabling principled, scalable, and automatic evaluation of attributions. Using our framework, we compare multiple attribution methods and observe consistent and quantitative differences amongst them across multiple learning strategies.

1 Introduction

The success of deep learning models, together with the difficulty of understanding how they work, has inspired a subfield of research on explaining predictions, often by highlighting specific input features deemed somehow important to a prediction (Ribeiro et al., 2016; Sundararajan et al., 2017; Shrikumar et al., 2017). For instance, an explanation generation method might highlight the spans "poorly acted" and "slow-moving" to explain the predicted "negative" label for a movie review. However, there is little agreement in the literature as to what constitutes a good explanation (Lipton, 2016). In addition, as shown in Table 1, various popular attribution methods disagree considerably regarding the set of explanatory tokens. The present situation in which multiple methods are claimed to confer the same property while offering such contrasting answers demands better articulations of desiderata

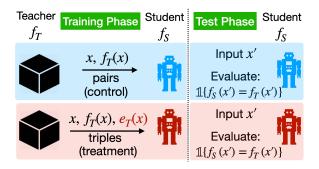


Figure 1: The proposed framework for evaluating explanation quality. Student models learn to mimic the teacher, with and without explanations (provided as "side information" with each example). Explanations are effective if they help students to better approximate the teacher on future test examples *for which such explanations are not available*. Students and teachers could be either models or people.

and better methods for *quantitatively* evaluating purported explanations at scale.

Many proposed explanation generation techniques evaluate their methods only by visually inspecting a handful of examples (Ribeiro et al., 2016; Sundararajan et al., 2017). While some recent approaches for evaluating explanations have been proposed, many of these can easily be gamed (Hooker et al., 2019; Treviso and Martins, 2020; Hase et al., 2020); and others rely heavily on model output for out-of-distribution samples (Poerner et al., 2018; De Young et al., 2020), violating the i.i.d. assumption in machine learning.

In this work, we propose a new metric, where explanations are evaluated by the degree to which they help a student model in learning to simulate the teacher on future examples, as outlined in Figure 1. To the best of our knowledge, our framework is the first to allow for scalable automatic evaluation of explanation quality in a principled way that

^{*}Work done during an internship at Google.

¹See §5 for a comprehensive discussion of existing metrics, and how they can be gamed by trivial strategies.

$oldsymbol{e}_{T}^{(i)}(oldsymbol{x}) ackslash oldsymbol{e}_{T}^{(j)}(oldsymbol{x})$	Random	Grad Norm	$Grad \times Input$	LIME	Integrated Gradients	Attention
Random	1.00	0.10	0.10	0.10	0.10	0.10
Grad Norm	0.10	1.00	0.27	0.13	0.22	0.30
$Grad \times Input$	0.10	0.27	1.00	0.11	0.16	0.17
LIME	0.10	0.13	0.11	1.00	0.16	0.15
Integrated Gradients	0.10	0.22	0.16	0.16	1.00	0.24
Attention	0.10	0.30	0.17	0.15	0.24	1.00

Table 1: Overlap among the top-10% tokens selected by different explanation techniques for sentiment analysis. For each explanation, we tabulate the fraction of tokens overlapping with other explanations: $\frac{|e_T^{(i)}(\boldsymbol{x}) \cap e_T^{(j)}(\boldsymbol{x})|}{|e_T^{(i)}(\boldsymbol{x})|}$

cannot be trivially gamed. Our method is based on argumentative models for justifying human reasoning: briefly, these models posit that the purpose of human explanations is to communicate information about how decisions are made (Mercier and Sperber, 2017). Our framework is similar to human studies conducted by Hase and Bansal (2020), who evaluate how explanations help predict model behavior. However, here we focus on protocols that do not rely on human-subject experiments.

Using our framework, we conduct extensive experiments on two NLP tasks: text classification and question answering. We compare two kinds of student models and multiple representative methods for producing explanations, spanning gradientbased saliency methods (Simonyan et al., 2013), integrated gradients (Sundararajan et al., 2017), LIME (Ribeiro et al., 2016) and attention-based explanations (Bahdanau et al., 2015). These comparisons lead to observable quantitative differences that make the relative merits of methods clear. For classification tasks, we find attention-based explanations to be the most effective, followed by integrated gradients, however, we do not find vanilla gradient-based saliency maps and LIME to be better than the no-explanations control. Unlike most prior work, we also explore the utility of explanations for question-answering tasks, where we evaluate the effectiveness of different student learners on both human-produced explanations collected by Lamm et al. (2020), and automatically generated explanations from a SpanBERT model (Joshi et al., 2020), obtaining quantitative results similar to those for classification tasks.

2 Explanation as communication

2.1 An Illustrative Example

In our framework, explanations are viewed as a communication channel between a teacher T and a student S, which serve the purpose of helping

S to predict T's outputs on a given input. As an example, consider the case of graduate admissions: an aspirant submits their application x and subsequently the admission committee T decides whether the candidate is to be accepted or not. The acceptance criterion, $f_T(x)$, represents a typical black box function—one that is of great interest to future aspirants. To *simulate* the admission criterion, a student S might study profiles of several applicants from previous iterations, x_1, \ldots, x_n , and their admission outcomes $f_T(x_1), \ldots, f_T(x_n)$. Let $A(f_S, f_T)$ be the simulation accuracy, the accuracy with which the student predicts the teacher's decisions on unseen future applications (defined formally below in §2.2).

Now suppose each previous admission outcome was supplemented with an additional explanation $e_T(\boldsymbol{x})$, from the admission committee, intended to help S understand the decisions made by T. Ideally, these explanations would enhance students' understanding about the admission process, and would help students simulate the admission decisions better, leading to a higher accuracy. We argue that the degree of improvement in simulation accuracy is a quantitative indicator of the utility of the explanations. Note that generic unfaithful explanations or explanations that simply encode the final decision (e.g., "We received far too many applications ...") are unlikely to help students simulate $f_T(\boldsymbol{x})$, as they provide no additional information.

2.2 Quantifiably Evaluating Explanations

For concreteness, we assume a classification task, and for a teacher T, we let f_T denote a model that computes the teacher's predictions. Let S be a student (either human or a machine), then T could teach S to simulate f_T by sampling

²Our illustrative example assumes that the admission decision solely depends upon the student application, and ignores how other competing applicants might affect the outcome.

n examples, x_1, \ldots, x_n and sharing with S a dataset \hat{D} containing its associated predictions $\{(x_1, \hat{y}_1), \ldots, (x_n, \hat{y}_n)\}$, where $\hat{y}_i = f_T(x_i)$, and S could then learn some approximation of f_T from this data:

$$f_{S,\hat{D}} = \operatorname{learn}(S,\hat{D})$$

Additionally, we assume that for a given teacher T, an explanation generation method can generate an explanation $e_T(x)$ for any example x which is some side information that potentially helps S in predicting $f_T(x)$. We use \hat{E} to denote a dataset of explanation-augmented examples, i.e.,

$$\hat{E} = \{(\boldsymbol{x}_1, \boldsymbol{e}_T(\boldsymbol{x}_1), \hat{y}_1), \dots, (\boldsymbol{x}_n, \boldsymbol{e}_T(\boldsymbol{x}_n), \hat{y}_n)\}$$

and the student learner can make use of this side information during training, to learn a classifier

$$f_{S|\hat{E}} = \text{learn}(S, \hat{E})$$

Note that none of the learning tasks discussed above involve the "gold" label y for any instance x, only the prediction \hat{y} for x, produced by the teacher. While the student S can use the explanations for learning, all the classifiers f_T , $f_{S,\hat{D}}$, and $f_{S,\hat{E}}$ predict labels given only the input x, without using the explanations, i.e., explanations are only available during training, not at test time.

In our framework the benefit of explanations is measured by how much they help the student to simulate the teacher. In particular, we quantify the ability of a student f_S to simulate a teacher using the *simulation accuracy*—the expected agreement between the student and teacher predictions:

$$A(f_S, f_T) = \mathbf{E}_{x} [1\{f_S(x) = f_T(x)\}],$$
 (1)

where the expectation is computed over test examples. Better explanations will lead to higher values of $A(f_{S,\hat{E}},f_T)$. Clearly, explanations are of no value unless this quantity is higher than the accuracy associated with learning to simulate the teacher without explanations, i.e. $A(f_{S,\hat{D}},f_T)$.

2.3 Automated Teachers and Students

In principle, T and S could be either people or algorithms. However, quantitative measurements are easier to conduct when T, and especially S are algorithms. In particular, imagine that T identifies an explanation $e_T(x)$ that is some subset of tokens in a document x that are relevant to the prediction (acquired by, for example, any of the explanation methods mentioned in the introduction) and S is

some machine learner that makes use of the explanation. Then the value of teacher-explanations for S can be assessed via standard evaluation of explanation-aware student learners, using predicted labels instead of gold labels. This value can then be compared to other schemes for producing explanations (e.g., integrated gradients).

One apparent "bug" in this framework is that in the automated case, one could obtain a perfect simulation accuracy with an explanation that communicates all the weights of the teacher classifier f_T to the student.³ We propose two approaches to address this problem. One is simply to limit explanations to be of a form that people can comprehend e.g., to limit explanations to spans in a document x. A second approach is motivated by the observation that people may find a concept difficult to explain when they are unaware of the student's prior knowledge (as any human educator will appreciate). To capture this we could assume that S is drawn from a distribution of students Pr(S), and extend our metric by considering expected benefit for a random student. Practically, simply experimenting with a small diverse set of students (e.g., networks with different sizes or architectures) would preclude trivial weight-copying solutions.

2.4 Discussion

In our framework, two design choices are crucial: (i) students do not have access to explanations at test time; and (ii) we use a machine learning model as a substitute for student learner. These two design choices differentiate our framework from similar communication games proposed by Treviso and Martins (2020) and Hase and Bansal (2020). When explanations are available at test time, they can leak the teacher output directly or indirectly, thus corrupting the simulation task. Both genuine and trivial explanations can encode the teacher output, making it difficult to discern the quality of explanations.4 The framework of Treviso and Martins (2020) is affected by this issue, which is probably only partially addressed by enforcing constraints on the student. Preventing access to explanations while testing solves this problem and offers flexi-

³All the weights of the model can be thought of as a complete explanation, and is a reasonable choice for simpler models, e.g., a linear-model with a few parameters.

⁴A trivial explanation may highlight the first input token if the teacher output is 0, and the second token if the output is 1. Such explanations, termed as "Trojan explanations", are a problematic manifestation of several approaches, as discussed in (Chang et al., 2020; Jacovi and Goldberg, 2020).

Sentiment Analysis (Zaidan et al., 2007)

I don't know what movie the critics saw, but it wasn't this one. The popular consensus among newspaper critics was that this movie is unfunny and dreadfully boring. In my personal opinion, **they couldn't be more wrong** If you were expecting Airplane! - like laughs and Agatha Christie - intense mystery, then yes, this movie would be a disappointment. However, if you're just looking for an enjoyable movie and a good time, **this is one to see** ...

Question Answering (Lamm et al., 2020)

Question: who plays mabel 's voice on gravity falls

Passage: Kristen Joy Schaal (born January 24, 1978) is an American actress, voice actress, comedian and writer. She is best known for her roles of Mel in Flight of the Conchords, the over-sexed nurse Hurshe Heartshe on The Heart, She Holler, Louise Belcher in Bob's Burgers, **Mabel Pines** in **Gravity Falls**, and Carol in The Last Man on Earth.

Table 2: Example of annotated rationales in sentiment analysis and referential equalities in question answering.

bility in choosing student models.

Substituting machine learners for people allows us to train student models on thousands of examples, in contrast to the study by Hase and Bansal (2020), where (human) students were trained only on 16 or 32 examples. As a consequence, the observed differences among many explanation techniques were statistically insignificant in their studies. While human subject experiments are a valuable complement to scalable automatic evaluations, it is expensive to conduct sufficiently large-scale studies; and people's preconceived notions might impair their ability to simulate the models accurately;⁵ and lastly these preconceived notions might bias performance for different people differently.

3 Learning with Explanations

Our student-teacher framework does not specify how to use explanations while training the student model. Below, we examine two broad approaches to incorporate explanations: attention regularization and multi-task learning. Our first approach regularizes attention values of the student model to align with the information communicated in explanations. In the second method, we pose the learning task for the student as a joint task of prediction and explanation generation, expecting to improve prediction due to the benefits of multitask learning. We show that both of these methods indeed improve student performance when using human-provided explanations (and gold labels) for classification tasks. We explore variants of these two approaches for question answering tasks.

Classification Tasks The training data for the student model consists of n documents x_1, \ldots, x_n , and the output to be learned, y_1, \ldots, y_n , comes

from the teacher, i.e. $y_i = f_T(\boldsymbol{x}_i)$, along with teacher-explanations $e_T(\boldsymbol{x}_1), \dots, e_T(\boldsymbol{x}_n)$. In this work, we consider teacher explanations in the form of a binary vector $e_T(\boldsymbol{x}_i)$, such that $e_T(\boldsymbol{x}_i)_j = 1$ if the j^{th} token in document \boldsymbol{x}_i is a part of the teacher-explanation, and 0 otherwise. To incorporate explanations during training, we suggest two different approaches. First, we use **attention regularization**, where we add a regularization term to our loss to reduce the KL divergence between the attention distribution of the student model $(\boldsymbol{\alpha}_{\text{student}})$ and the distribution of the teacher-explanation $(\boldsymbol{\alpha}_{\text{exp}})$:

$$\mathcal{R}' = -\lambda \text{ KL}(\alpha_{\text{exp}} \parallel \alpha_{\text{student}}), \qquad (2)$$

where the explanation distribution (α_{exp}) is uniform over all the tokens in the explanation and ϵ elsewhere (where ϵ is a very small constant). When dealing with student models that employ multiheaded attention, which use multiple different attention vectors at each layer of the model (Vaswani et al., 2017), we take $\alpha_{student}$ to be the attention from the <code>[CLS]</code> token to other tokens in the last layer, averaged across all attention heads.

Second, we use explanations via **multi-task learning**, where the two tasks are prediction and explanation generation (a sequence labeling problem). Formally, the overall loss can be written as:

$$L = -\sum_{i=1}^{n} \left[\log \underbrace{p(y_i | \boldsymbol{x_i}; \theta)}_{\text{classify}} + \log \underbrace{p(\boldsymbol{e_i} | \boldsymbol{x_i}; \phi, \theta)}_{\text{explain}} \right]$$

As in multi-task learning, if the task of prediction and explanation generation are complementary, then the two tasks would benefit from each other. As a corollary, if the teacher-explanations offer no additional information about the prediction, then we would see no benefit from multi-task learning (appropriately so). For all our classification experiments, we use BERT (Devlin et al., 2019) with

⁵We speculate this effect to be pronounced when the models' outputs and the true labels differ only over a few samples.

a linear classifier on top of the <code>[CLS]</code> vector to model $p(y|x;\theta)$. To model $p(e|x;\phi|\theta)$ we use a linear-chain CRF (Lafferty et al., 2001) on top of the sequence vectors from BERT. Note that we share the BERT parameters θ between classification and explanation tasks. In prior work, similar multi-task formulations have been demonstrated to effectively incorporate rationales to improve classification performance (Zaidan and Eisner, 2008) and evidence extraction (Pruthi et al., 2020).

Question Answering Let the question q consist of m tokens $q_1 \ldots q_m$, along with passage x that provides the answer to the question, consisting of n tokens x_1, \ldots, x_n . Let us define a set of question phrases \mathcal{Q} and passage phrases \mathcal{P} to be

$$Q = \{(i, j) : 1 \le i \le j \le m\}$$

$$P = \{(i, j) : 1 \le i \le j \le n\}$$

We consider a subset of QED explanations (Lamm et al., 2020), which consist of a sequence of one or more "referential equality annotations" $e_1 \dots e_{|e|}$. Formally, each referential equality annotation e_k for $k=1\dots |e|$ is a pair $(\phi_k,\pi_k)\in\mathcal{Q}\times\mathcal{P}$, specifying that phrase ϕ_k in the question refers to the same thing in the world as the phrase π_k in the passage (see Figure 1).

To incorporate explanations for question answering tasks, we use the two approaches discussed for text classification tasks, namely attention regularization and multi-task learning. Since the explanation format for question answering is different from the explanations in text classification, we use a lossy transformation, where we we construct a binary explanation vector, where 1 corresponds to tokens that appear in one or more referential equalities and 0 otherwise. Given the transformation, both these approaches do not use the alignment information present in the referential equalities.

To exploit the alignment information provided by referential equalities, we introduce the **attention alignment loss** term:

$$\mathcal{R}^{'} = -\lambda \log \left(rac{1}{|e|} \sum_{k=1}^{|e|} oldsymbol{lpha}_{ ext{student}} [\phi_k
ightarrow \pi_k]
ight),$$

where $e_k = (\phi_k, \pi_k)$ is the k^{th} referential equality, and $\alpha_{\text{student}}[\phi_k \to \pi_k]$) is the last layer average attention originating from tokens in ϕ_k to tokens in π_k . The average is computed across all the tokens in ϕ_k and across all attention heads. The underlying

idea is to increase attention values corresponding to the alignments provided in explanations.

4 Results & Discussion

Below, we discuss the results upon applying our framework to explanations and output from human teachers and automated teachers.

4.1 Human Experts as Teachers

To establish that high quality explanations indeed improve the student models' performance, we apply these methods to explanations and outputs from human experts. There exist a few tasks where researchers have collected explanations from experts besides the output label. In one such task on sentiment analysis, Zaidan et al. (2007) collected "rationales" where people highlighted portions of the movie reviews that would encourage (or discourage) readers to watch (or avoid) the movie. In a recent effort, Lamm et al. (2020) collected "QED annotations" over questions and the passages from the Natural Questions (NQ) dataset (Kwiatkowski et al., 2019). These annotations contain the salient entity in the question and their referential mentions in the passage that need to be resolved to answer the question. For both these tasks, our studentlearners are pretrained BERT models, which are further fine-tuned with outputs and explanations from human experts.

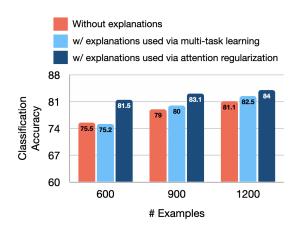


Figure 2: Learning with explanations from experts for sentiment analysis. We note that attention regularization leads to large improvements, whereas multi-task learning requires more examples to yield gains.

Results Our suggested methods to learn from explanations indeed benefit from human explanations. For the sentiment analysis task, attention regularization boosts performance, as depicted in Figure 2.

For instance, attention regularization improves the accuracy by an absolute 6 points, for 600 examples. The performance benefits, unsurprisingly, diminish with increasing training examples—for 1200 examples, the attention regularization improves performance by 2.9 points. While attention regularization is immediately effective, the multi-task learning requires more examples to learn the sequence labeling task. We do not see any improvement using multi-task learning for 600 examples, but for 900 and 1200 training examples, we see absolute improvements of 1 and 1.4 points, respectively.

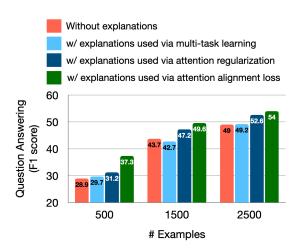


Figure 3: Learning with explanations from experts for question answering tasks.

For the question-answering task, we measure the F1 score of our student models on the test set carved from the QED dataset. As one can observe from Figure 3, both attention regularization and attention alignment loss improve the performance drastically, whereas multi-task learning is not effective.⁶ Attention regularization and attention alignment loss improve F1 score by 2.3 and 8.4 points for 500 examples, respectively. The gains decrease with increasing examples (e.g., the improvement due to attention alignment loss is 5 points on 2500 examples, compared to 8.4 points with 500 examples). The key takeaway from these two experiments (with explanations and outputs from human experts) is that we observe benefits with the learning procedures discussed in previous section. This provides support to our proposal to use these methods for evaluating various explanation techniques.

4.2 Automated Teacher

Setup Instead of human experts, here we use machine learning models as teachers. For sentiment analysis task, we use BERT (Devlin et al., 2019) as our teacher model, and examine the effectiveness of five commonly used methods for producing explanations, including LIME (Ribeiro et al., 2016), gradient-based saliency methods (i.e., gradient norm and gradient × input) (Simonyan et al., 2013), integrated gradients (Sundararajan et al., 2017) and attention-based explanations (Bahdanau et al., 2015). For each explanation technique to be comparable to others, we sort the tokens as per scores assigned by a given explanation technique, and use only the top-k% tokens.⁸ This also ensures that, across different explanations, the quantity of information from the teacher to the student per example is constant. Additionally, we evaluate no-explanation, random-explanation and trivialexplanation baselines. For random explanations, we randomly choose k% tokens, and for trivial explanations, we use the first k% tokens for the positive class, and the next k% tokens for the negative class. Such trivial explanations encode the label and can achieve perfect scores for many evaluation protocols that use explanations at test time. Corresponding to each explanation type, we train a student model—also a BERT model—using outputs and explanations from the teacher. For this task, we use the movie reviews from IMDb collected by Maas et al. (2011). The training set of the original dataset is used to train the teacher model, and the original test set is split to construct train, development and test sets for the student model.

For question answering task, we use the Natural Questions dataset (Kwiatkowski et al., 2019). The teacher model is a SpanBERT-based model that is trained jointly to answer the question and produce explanations (Lamm et al., 2020). We use the model made available by the authors. The test set of Natural Questions is carved to form the training, development and test set for the student model. Our student is a BERT-based QA model. We evaluate the effectiveness of the explanations produced by the Span-BERT teacher model.

⁶We speculate that multi-task learning might require more than 2500 examples to yield benefits. Unfortunately, for the QED dataset, we only have 2500 training examples.

⁷Details about explanation techniques are in Appendix A. ⁸We chose k to be 10, as people marked about 10% tokens in their rationales (Zaidan et al., 2007).

	attention regularization					multi-task learning					
Examples	500	1000	2000	4000	8000	•	500	1000	2000	4000	8000
No Explanation	90.0	91.5	92.6	93.6	94.9		90.0	91.5	92.6	93.6	94.9
Random Explanation	89.4	90.6	92.4	93.9	94.6		89.6	91.5	92.7	94.1	94.5
Trivial Explanation	78.5	82.8	88.3	92.3	93.5		86.1	90.6	91.5	93.4	93.8
LIME	90.2	91.3	92.6	94.0	94.8		90.2	91.3	92.6	94.0	95.0
Gradient Norm	90.4	91.6	92.4	92.7	93.7		88.8	92.3	93.1	94.3	94.2
Gradient × Input	90.5	91.7	92.2	93.6	94.7		89.3	91.2	92.7	94.4	94.5
Integrated Gradients	92.4	92.6	93.6	94.8	95.7		89.5	91.6	93.3	94.5	95.2
Attention	92.7	93.9	95.2	96.2	97.0		89.6	91.5	94.4	96.0	96.6

Table 3: Evaluating the effectiveness of explanation techniques for a text classification task using our student-teacher framework. We find attention-based explanations to be most effective, followed by integrated gradients.

Results From Table 3, we note that for the classification task, the attention-based explanations are the most effective, followed by integrated gradients. We also observe that LIME and other gradientbased saliency techniques do not yield better performance compared to no-explanation and randomexplanation controls. All the values in Table 3 are averaged over 5 random seeds. While it may seem that attention-based explanations are the most effective only because the process to incorporate explanations regularizes attention, this is not the case as trends from multi-task learning corroborate the same conclusion. We also evaluate explanations using a different (and bigger) student model (BERT large) and observe the same trends (see Appendix B). As previously noted, multi-task learning requires more examples to yield benefits, and hence we do not observe any quantitative differences for less than 1000 examples. This reaffirms that many training examples may be required for student models to tease apart differences among explanations, which is hard to achieve with human-subject experiments. Lastly, we see that trivial explanations do not outperform the control experiment, confirming that our metric is robust to such explanations. These explanations would result in a perfect score for protocols discussed in (Hase et al., 2020; Treviso and Martins, 2020; Hooker et al., 2019).

For the question answering task, we observe from Figure 4 that explanations from SpanBERT QA model are very effective, as indicated by both the approaches to learn from explanations. The performance benefit using attention alignment loss with 250 examples is 7.9 absolute points, and these gains decrease (unsurprisingly) with increasing number of training examples. For instance, the

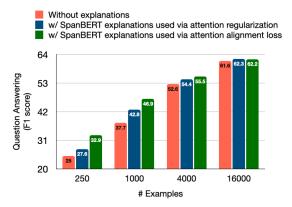


Figure 4: Evaluating the effectiveness of explanations from SpanBERT QA model. We find the explanations to be effective across both the learning strategies.

gain is only 2.9 points for 4000 examples and the benefits vanish with 16000 training examples.

5 Related Work

Building on the ideas in (Lipton, 2016), several past papers have suggested simulatability as an approach to measure interpretability. In their survey, Doshi-Velez and Kim (2017) propose the task of forward simulation: given an input and an explanation, people must predict what a model would output for that instance. Chandrasekaran et al. (2018) conduct human-studies to evaluate if explanations from Visual Question Answering (VQA) models help users predict the output. Recently, Hase and Bansal (2020) perform a similar human-study across text and tabular classification tasks. Due to the nature of these two studies, the observed differences with and without explanation, and amongst different explanation types, were not significant. Conducting large-scale human studies poses several challenges, including the

considerable financial expense and the logistical challenge of recruiting and retaining participants for unusually long tasks (Chandrasekaran et al., 2018). By automating *students* in our framework, we directly mitigate such challenges, and observe interesting (and consistent) quantitative differences among methods in our comparisons.

Closest in spirit to our work, Treviso and Martins (2020) propose a new framework to assess explanatory power as the communication success rate between an explainer and a layperson (which can be people or machines). However, as a part of their communication, they pass on explanations during test time, which could easily leak the label, and the models trained to play this communication game can learn trivial protocols (e.g., explainer generating a period for positive examples and a comma for negative examples). This is probably only partially addressed by enforcing constraints on the explainer and the explainee. Our setup does not face this issue as explanations are not available at test time.

To counter the effects of leakage due to explanations, Hase et al. (2020) present a Leakage-Adjusted Simulatability (LAS) metric. Their metric quantifies the difference in performance of the simulation models (analogous to our student models) with and without explanations *at test time*. To adjust for this leakage, they average their simulation results across two different sets of examples, ones that leak the label, and others that do not. Leakage is modeled as a binary variable, which is estimated by whether a discriminator can predict the answer using the explanation alone. It is unclear how the average of simulation results solves the problem, especially when most explanations leak the label.

Interpretability Benchmarks DeYoung et al. (2020) introduce ERASER benchmark to assess how well the rationales provided by models align with human rationales, and also how faithful these rationales are to model predictions. To measure faithfulness, they propose two metrics: comprehensiveness and sufficiency. They compute sufficiency by calculating the model performance using only the rationales, and comprehensiveness by measuring the performance without the rationales. This approach clearly violates the i.i.d assumption, as the training and evaluation data do not come from the same distribution. It is unclear whether the differences in model performance are due to distribution shift or because the features that were removed (or retained) are truly informative. This

concern is also highlighted by Hooker et al. (2019), who instead evaluate interpretability methods via their RemOve And Retrain (ROAR) benchmark. However, this method is not fail-safe, as this metric could be easily gamed: e.g., depending upon the prediction, an adversarial teacher could use a different pre-specified ordering of important pixels as an explanation. Our methods are robust to such gamification. Lastly, Poerner et al. (2018) present a hybrid document classification task, where the sentences are sampled from different documents with different class labels. The evaluation metric validates if the important tokens (as per a given interpretation technique) point to the tokens from the "right" document, i.e., one with the same label as the predicted class. This protocol too relies on model output for out-of-distribution samples (i.e., hybrid documents), and is very task specific.

6 Conclusion

We have formalized the value of explanations as their utility in a student-teacher framework, measured by how much they improve the student's ability to simulate the teacher. We consider a setting in which explanations are provided by the teacher as additional side information during training, but are not available at test time. This framework prevents "leakage" between explanations and output labels, which several of the past approaches suffer from, and hence our framework is harder to game than prior proposals. Our evaluation is also well-suited to automated studies, as it simply consists of running variants of standard machinelearning experiments. The framework hence makes it easy to confirm and measure the value of humanprovided explanations. Additionally, we can now conduct extensive experiments that measure the value of numerous previously-proposed schemes for producing explanations, including attention methods, gradient-based saliency methods, LIME and attention-based explanations. The experiments conducted result in clear quantitative differences between different explanation methods. Among explanation methods, we find attention-based explanations to be the most effective, followed by integrated gradients, and neither LIME nor other gradient-based methods outperform the control. For student models, we find that both multi-task and attention-regularized student learners are effective, but attention-based learners are more effective, particularly in low-resource settings.

Acknowledgements

We are grateful to Jasmijn Bastings, Katja Filippova, Matthew Lamm, Patrick Verga, Rachit Bansal and Slav Petrov for insightful discussions that shaped this work. We thank Chris Alberti for sharing explanations from the SpanBERT model.

References

- Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. *ICLR*.
- Arjun Chandrasekaran, Viraj Prabhu, Deshraj Yadav, Prithvijit Chattopadhyay, and Devi Parikh. 2018. Do explanations make vqa models more predictable to a human? *arXiv preprint arXiv:1810.12366*.
- Shiyu Chang, Yang Zhang, Mo Yu, and Tommi S Jaakkola. 2020. Invariant rationalization. *arXiv* preprint arXiv:2003.09772.
- Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.
- Jay DeYoung, Sarthak Jain, Nazneen Fatema Rajani, Eric Lehman, Caiming Xiong, Richard Socher, and Byron C. Wallace. 2020. ERASER: A benchmark to evaluate rationalized NLP models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4443–4458, Online. Association for Computational Linguistics.
- Finale Doshi-Velez and Been Kim. 2017. Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*.
- Peter Hase and Mohit Bansal. 2020. Evaluating explainable AI: Which algorithmic explanations help users predict model behavior? In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5540–5552, Online. Association for Computational Linguistics.
- Peter Hase, Shiyue Zhang, Harry Xie, and Mohit Bansal. 2020. Leakage-adjusted simulatability: Can models generate non-trivial explanations of their behavior in natural language? *Findings of EMNLP*.
- Sara Hooker, Dumitru Erhan, Pieter-Jan Kindermans, and Been Kim. 2019. A benchmark for interpretability methods in deep neural networks. In *Advances in Neural Information Processing Systems*, pages 9737–9748.

- Alon Jacovi and Yoav Goldberg. 2020. Aligning faithful interpretations with their social attribution. *arXiv* preprint arXiv:2006.01067.
- Mandar Joshi, Danqi Chen, Yinhan Liu, Daniel S Weld, Luke Zettlemoyer, and Omer Levy. 2020. Spanbert: Improving pre-training by representing and predicting spans. *Transactions of the Association for Com*putational Linguistics, 8:64–77.
- Tom Kwiatkowski, Jennimaria Palomaki, Olivia Redfield, Michael Collins, Ankur Parikh, Chris Alberti, Danielle Epstein, Illia Polosukhin, Jacob Devlin, Kenton Lee, et al. 2019. Natural questions: a benchmark for question answering research. *Transactions of the Association for Computational Linguistics*, 7:453–466.
- John Lafferty, Andrew McCallum, and Fernando CN Pereira. 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data. 18th International Conference on Machine Learning 2001 (ICML 2001).
- Matthew Lamm, Jennimaria Palomaki, Chris Alberti, Daniel Andor, Eunsol Choi, Livio Baldini Soares, and Michael Collins. 2020. Qed: A framework and dataset for explanations in question answering. arXiv preprint arXiv:2009.06354.
- Zachary C Lipton. 2016. The mythos of model interpretability. *Queue*, 16(3):31–57.
- Andrew L. Maas, Raymond E. Daly, Peter T. Pham, Dan Huang, Andrew Y. Ng, and Christopher Potts. 2011. Learning word vectors for sentiment analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, pages 142–150, Portland, Oregon, USA. Association for Computational Linguistics.
- Hugo Mercier and Dan Sperber. 2017. *The enigma of reason*. Harvard University Press.
- Nina Poerner, Hinrich Schütze, and Benjamin Roth. 2018. Evaluating neural network explanation methods using hybrid documents and morphosyntactic agreement. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 340–350, Melbourne, Australia. Association for Computational Linguistics.
- Danish Pruthi, Bhuwan Dhingra, Graham Neubig, and Zachary C Lipton. 2020. Weakly-and semi-supervised evidence extraction. *Findings of EMNLP*.
- Marco Tulio Ribeiro, Sameer Singh, and Carlos Guestrin. 2016. "why should i trust you?" explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, pages 1135–1144.

- Avanti Shrikumar, Peyton Greenside, and Anshul Kundaje. 2017. Learning important features through propagating activation differences. *arXiv preprint arXiv:1704.02685*.
- Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. 2013. Deep inside convolutional networks: Visualising image classification models and saliency maps. *arXiv preprint arXiv:1312.6034*.
- Mukund Sundararajan, Ankur Taly, and Qiqi Yan. 2017. Axiomatic attribution for deep networks. *arXiv* preprint arXiv:1703.01365.
- Marcos V Treviso and André FT Martins. 2020. Towards prediction explainability through sparse communication. *arXiv* preprint arXiv:2004.13876.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008.
- Omar Zaidan and Jason Eisner. 2008. Modeling annotators: A generative approach to learning from annotator rationales. In *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 31–40, Honolulu, Hawaii. Association for Computational Linguistics.
- Omar Zaidan, Jason Eisner, and Christine Piatko. 2007. Using "annotator rationales" to improve machine learning for text categorization. In *Human language technologies 2007: The conference of the North American chapter of the association for computational linguistics; proceedings of the main conference*, pages 260–267.

Supplementary Material

A Explanation Types

We experiment with the following explanation techniques for text classification. For each explanation type, we use the top-10% tokens.

LIME Locally Interpretable Model-agnostic Explanations (Ribeiro et al., 2016), or LIME, are explanations produced by a linear interpretable model that is trained to approximate the original black box model in the local neighborhood of the input example. For a given example, several samples are constructed by perturbing the input string, and these samples are used to train the linear model. For our experiments, we draw twice as many samples as the number of tokens in the example, and select the top words that explain the predicted class. We set the number of features for the linear classifier to be 2k, where k is the number of tokens to be selected. Other parameters are set to default values.

Gradient-based Saliency Methods Several papers, both in NLP and computer vision, use gradients of the log-likelihood of the predicted label to understand the effect of infinitesimally small perturbations in the input. While no perturbation of an input string is infinitesimally small, nonetheless, researchers have continued to use this metric. It is most commonly used in two forms: grad norm, i.e., the ℓ_2 norm of the gradient w.r.t. the token representation, and grad \times input (also called grad dot), i.e., the dot product of the gradient w.r.t the token representation and the token representation.

Integrated Gradients Gradients capture only the effect of perturbations in an infinitesimally small neighborhood, integrated gradients (Sundararajan et al., 2017), instead compute and integrate gradients of the log-likelihood of the predicted class along the line joining a starting reference point and the given input example. In our experiments, for each example, we integrate the gradients over 50 different points on the line.

Attention-based Explanations Attention mechanisms were originally introduced by (Bahdanau et al., 2015) to align source and target tokens in neural machine translation. For sequence to sequence tasks, to generate the target token, the decoder hidden representation is utilized as a *query vector* and its dot product with each of the source tokens' representations (the key vectors) are taken to be similarity scores. These similarity scores are scaled and

normalized (typically via the softmax operation) and the resulting values (on the simplex) are used to compute a weighted sum over the source tokens' representations to produce the value vector that is used for prediction. For classification tasks, a learnable vector is treated as a query vector. Because attention mechanisms allocate weight among the encoded tokens, these coefficients are sometimes thought of intuitively as indicating which tokens the model *focuses on* when making a prediction.

B Different Student Models

As discussed in §2.3, to preclude trivial weight-copying solutions, one could practically use different types of student models. Here, we use a larger student model, i.e. BERT large to assess the efficacy of different explanation techniques. From Table 4 we note that attention-based explanations are most effective, followed by integrated gradients. These trends are consistent with the results obtained using BERT base model as our student model (in Table 3).

	attention regularization						
Examples	500	1000	2000	4000			
No Explanation	91.7	92.6	93.0	93.7			
LIME	92.2	92.7	93.1	94.3			
Gradient Norm	92.3	92.9	93.1	93.3			
Gradient × Input	92.2	93.0	93.7	94.4			
Integrated Gradients	93.3	93.4	94.4	95.2			
Attention	93.5	94.0	95.4	95.5			

Table 4: Evaluating the effectiveness of explanation techniques for sentiment analysis using a bigger student model (BERT large). Consistent with the other student model, we find attention-based explanations to be most effective, followed by integrated gradients.