What to Learn, and How: Toward Effective Learning from Rationales

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Abstract
Learning from rationales seeks to augment model training with human-provided rationales (i.e., a subset of input tokens) that justify those labels. While intuitive, this idea has proven elusive in practice. We make two observations about human rationales via empirical analyses: 1) maximizing predicted rationale accuracy is not necessarily the optimal objective for improving model performance; 2) human rationales vary in whether they provide sufficient information for the model to exploit for prediction, and we can use this variance to assess a dataset’s potential improvement from learning from rationales. Building on these insights, we propose loss functions and learning strategies, and evaluate their effectiveness on three datasets with human rationales. Our results demonstrate consistent improvements over baselines in both label performance and rationale performance, including a 3% accuracy improvement on MultiRC. Our work highlights the importance of understanding properties of human explanations and exploiting them accordingly in model training.

1 Introduction

Learning from human explanations is an important problem. Explanations can directly address spurious or unjust feature associations in models by serving as additional training signal to ground-truth labels. They can provide signal for not only what to predict but also how to predict, and thus potentially improve model accuracy, robustness and fairness (Hase and Bansal, 2021).

The idea has intuitive appeal. When a model makes an error, it should be possible to examine its internal logic, discover the root of that error, and use our own knowledge to correct the model’s behavior directly. In this work we consider explanations in the form of rationales — subsets of the input tokens chosen to explain the prediction.

Generally, learning from rationales (LFR) in NLP aims to improve model performance by using human rationales to teach the model which tokens to use and which tokens to ignore. It typically involves some kind of rationale supervision objective in addition to its primary label prediction objective, with the hope that optimizing toward the former can improve generalization performance on the latter.

Unfortunately, this goal has proven elusive. Many studies have found that learning from rationales hurts model performance, or that any improvement is marginal or limited to secondary goals like explanation quality (Plumb et al., 2020; Ross et al., 2017; Zaidan et al., 2007).

In this paper, we analyze the relationship between human rationale properties and model performance by examining how prediction accuracy responds to differing levels of oracle access to such rationales. From this analysis we develop two general observations about learning from rationales which we believe will prove useful in solving this important problem.

Our first observation is that rationale prediction accuracy is not necessarily the right objective to improve label prediction performance in LFR. That is, while a human rationale as a whole may bear useful signal for label prediction, not every rationale token (or omission) is equally useful and we may be doing ourselves a disservice by weighting them equally in rationale supervision. For example, we find empirically that recall seems to mediate rationale utility more strongly than precision.

Second, we find that within a given rationale dataset, certain rationales are more helpful and certain rationales less helpful. Specifically, certain rationales contain sufficient signal for a model to make an accurate prediction when using only those rationale tokens, while certain rationales do not. Empirically measuring this ratio gives us a limit for how much learning from rationales could improve model performance on a given dataset—if we could perfectly emulate human rationales. Our experiment results mirror these quasi-upper bounds. This
observation also suggests a “selective supervision” learning strategy that focuses on the “good” rationales at the expense of the “bad” rationales, not bothering to learn from human rationales that will only hinder the model.

We operationalize these observations as modifications to a rationale-style model (Lei et al., 2016), also known as BERT-to-BERT (DeYoung et al., 2020). The first BERT is used to extract a rationale from the input (with or without supervision), and the second BERT predicts the label given the predicted rationale as a mask on the input. This type of model is a straightforward approach to learning from rationales, with the rationale supervision being applied to the extractor and the prediction supervision to the predictor.

We test four modifications, three diverging from strict token-wise accuracy in the rationale supervision objective (first observation), and one which implements “selective supervision,” ignoring useless rationales in training (second observation).

Evaluating on three datasets, our proposed methods produce varying levels of improvement over a baseline BERT model, ranging from substantial for MultiRC (3%) to marginal for E-SNLI (0.4%). This improvement is more salient compared to a baseline rationale model, as our methods mitigate issues associated with a naive approach to rationale supervision. Additionally, our methods also improve rationale prediction performance.

Taken together, our results demonstrate the importance of considering the variance of predictive utility both between and within human rationales as a source of additional training signal, an observation not present in prior work on the subject. Our proposed modifications produce incremental improvements and help pave the way toward truly effective and general learning from rationales.

2 Related Work

2.1 Explanation Methods

Numerous methods have been proposed in recent years for explaining model prediction, most frequently attribution-style approaches which seek to attribute model prediction to subsets of the input (Murdoch et al., 2019; Vilone and Longo, 2020).

Posthoc approaches are applied retroactively to a trained model. These range from perturbation-based methods such as LIME (Ribeiro et al., 2016) and SHAP (Lundberg and Lee, 2017) to analytical methods such as saliency (Simonyan et al., 2013) and integrated gradients (Sundararajan et al., 2017).

By contrast, attention methods generate attribution masks jointly with prediction. These methods are often designed for performance, e.g. neural translation (Bahdanau et al., 2014) and BERT (Devlin et al., 2018), then co-opted for analysis, e.g., Jain and Wallace (2019); Clark et al. (2019).

A subset of attention methods, rationale-style methods, generate a binary attention mask across the input as an explicit nod toward interpretability. Lei et al. (2016) and Zhang et al. (2016) are early neural examples. More recent work has extended these basic approaches with adversarial training (Yu et al., 2019; Carton et al., 2018; Sha et al., 2020), hybridization with posthoc approaches (Jain et al., 2020), and consideration for syntactic structure (Glockner et al., 2020). We use this family of models in our study.

2.2 Learning from Explanations

As interest in model explanations has blossomed, so has interest in human explanations as additional training data (Wiegreffe and Marasović, 2021). Many recent datasets have been released with both document labels and human rationales for those labels, a number of which have been collected into ERASER (DeYoung et al., 2019).

Early work in learning from human explanations includes Zaidan et al. (2007) and Druck et al. (2009), as well as a line of work termed “explanatory debugging” (Kulesza et al., 2015; Lertvittayakumjorn and Toni, 2021). More recent work spans a variety of approaches, categorized by Hase and Bansal (2021) into regularization (e.g., Ross et al. (2017)), data augmentation (e.g., Hancock et al. (2018)), and supervision over intermediate outputs (e.g., DeYoung et al. (2019)).

Unfortunately, improvements to model accuracy as a result of explanation learning have proven elusive. Studies occasionally claim such improvement, such as Rieger et al. (2020), which observes general improvements on a medical vision task. More commonly their claims pertain to secondary objective such as explanation quality (e.g., Plumb et al. (2020)), robustness (e.g. Ross et al. (2017), Srivastava et al. (2020)), or few-shot learning (e.g., Yao et al. (2021)). Hase and Bansal (2021) gives an overview of the problem and discusses circumstances under which learning from explanations is liable to work. Our paper contributes to this line of work by considering research questions not cov-
Table 1: Basic statistics of the datasets.

| Dataset   | Text length | Rationale length | Rationale granularity |
|-----------|-------------|------------------|-----------------------|
| MultiRC   | 336.0       | 52.0             | sentence              |
| FEVER     | 355.9       | 47.0             | sentence              |
| E-SNLI    | 23.5        | 6.1              | token                 |

We consider three datasets in this work. All three are document-query text comprehension tasks, where the task is to determine whether the query is true or false given the document. We use the train, development, test splits offered by DeYoung et al. (2019). Table 1 shows the basic statistics of each dataset based on the training set.

- **MultiRC** (Khashabi et al., 2018). A reading comprehension dataset of 32,091 document-question-answer triplets that are true or false. Rationales consist of 2-4 sentences from a document that are required to answer the given question.
- **FEVER** (Thorne et al., 2018). A fact verification dataset of 76,051 snippets of Wikipedia articles paired with claims that they support or refute. Rationales consist of a single contiguous sub-snippet, so the basic unit of rationale is sentence.
- **E-SNLI** (Camburu et al., 2018). A textual entailment dataset of 568,939 short snippets and claims for which each snippet either refutes, supports, or is neutral toward. Input texts are much shorter than MultiRC and FEVER, and rationales are at the token level.

4 Analysis

To understand properties of human rationales for the purpose of learning from rationales, we analyze the effect of human rationales when they are used as inputs to a trained model.

4.1 Human Rationales can Improve Performance

A basic question about the viability of learning from rationales is whether human rationales bear the potential for improving model performance. That is, do human explanations successfully reveal useful tokens while occluding confounding tokens, such that a model evaluated only on the revealed tokens is able to get improved performance relative to the full input? We refer to such rationale-redacted inputs as rationalized inputs.

We define sufficiency-accuracy (SA) as how accurate the model is across a corpus of rationalized input. This is an aggregate measure, similar to sufficiency as defined in DeYoung et al. (2019) but focused on absolute performance rather than similarity to baseline model output. We refer to the sufficiency-accuracy of the human rationales as human sufficiency-accuracy (HSA).

Given a rationale, human or model-generated, a natural way to use it is to only keep the tokens in the rationale and fully remove the other tokens. An alternative is to substitute tokens that are not in the rationale with the [MASK] token, as is done during MASK-LM pretraining (Devlin et al., 2018). The advantage of the latter is that it can be done in a differentiable manner, such as in our BERT-to-BERT architecture. Thus, as we evaluate the sufficiency-accuracy of human rationales, we do so for both token removal and [MASK] token substitution.

Fig. 1a shows that removing all non-human-rationale tokens improves model performance by almost 6% for MultiRC, which suggests that human rationales indeed have the potential to improve model performance on this dataset. Meanwhile, doing this has virtually no effect on FEVER, while it dramatically decreases performance on E-SNLI. Performing [MASK] substitution has a negative effect on all three models, presumably because the presence of [MASK] tokens is a greater distribution shift than the removal of non-rationale tokens.

If that distribution shift from full inputs to rationalized inputs has a negative impact on the apparent value of human rationales, then we can repeat this analysis for models trained on both rationalized and full inputs. As Fig. 1b shows, such adaptation brings the two masking strategies back to parity and reverses their effect on E-SNLI.

However, even with adaptation, human rationales do not enable the model to infer the correct label for over 20% of instances in MultiRC, indicating the limit of learning from rationales. This adaptation does come with the risk of overfitting to the presence of human rationales. Indeed, rationale annotation had different criteria for different classes in E-SNLI, so the near-perfect HSA on the adapted model probably reflects this idiosyncrasy.

So: if our model were able to perfectly emulate human rationales, we could observe substantial potential for label accuracy improvement on Mul-
tiRC, mild potential at best for FEVER, and little or no potential for E-SNLI. This gives us a guide to whether learning from rationales is plausible for a given dataset. However, just like label prediction, there will always be a limit to the accuracy of rationale prediction, so it is sensible to ask how potential improvement in the former responds to imperfect performance on the latter.

4.2 Importance of Rationale Accuracy

We focus on MultiRC, where evaluating a standard fine-tuned BERT model on human-rationalized data results in a sufficiency-accuracy of 74%, a significant improvement over the normal test accuracy of 68%. But how robust is this improvement to rationale prediction error? We examine how the sufficiency-accuracy of human rationales changes as they are corrupted by random addition, dropping, and swapping of tokens.

In this analysis, an $N\%$ drop removes $N\%$ of tokens from each rationale in the dataset, reducing recall to $100 - N$. An $N\%$ addition adds tokens numbering $N\%$ the size of each rationale, from the set of non-rationale tokens, reducing precision to $100 - (100 + N)$. An $N\%$ swap performs both operations, swapping $N\%$ of rationale tokens for the same number of non-rationale tokens.

The “dropped” curve in Fig. 2a shows that human rationales afford improved accuracy over the baseline until roughly 40% of tokens have been dropped from them, suggesting that a minimum of 60% recall is needed derive an advantage from human rationales over the full input. Per the “added” curve, adding the same number of irrelevant tokens to the rationale has a much less severe impact on accuracy, suggesting that errors of omission are significantly worse than errors of inclusion for learning from rationales.

Fig. 2b and 2c respectively show the effect of this perturbation on high- and low-sufficiency-accuracy human rationales, which constitute 74% and 26% of rationales respectively for this model. High-SA rationales follow a similar trend to the whole population, but the recall requirement is lower than Fig. 2a to exceed model accuracy with the full input (the “dropped” curve meets the blue line at 50%). In comparison, low-SA rationales demonstrate interesting properties. These rationales actually have a sabotaging effect: the model would have an accuracy of 27% with the full input, which is lowered to 0% by the presence of these rationales. Also, addition and dropping have a similar effect in mitigating this sabotage. Similar results hold on FEVER and E-SNLI except the apparent required recall is much higher ($>90\%$) for both methods (see the appendix), again indicating challenges for learning from rationales.

In summary, our analyses inspire two general observations about learning from rationales: 1) moving away from naive accuracy (toward recall, for example) as a rationale supervision objective, and 2) focusing on useful rationales over harmful ones.
5 Methods

Equipped with these insights, we propose strategies for learning from rationales. We will release our code at [anonymized url] upon publication.

5.1 Background and Baseline Models

We start by introducing the background and the baseline models. Our training data include input tokens, their corresponding rationales, and labels. Formally, an instance is denoted as \((x, \alpha, y)\), where \(x = (x_1, \ldots, x_L)\) is a text sequence of length \(L\) and human rationale \(\alpha\) of the same length. \(\alpha_i = 1\) indicates that token \(x_i\) is part of the rationale, \(\alpha_i = 0\) otherwise.

We use HuggingFace’s BERT-base-uncased (Devlin et al., 2018; Wolf et al., 2020) as the basis for our experiments and analysis. Used in the standard way, BERT ignores \(\alpha\) and is fine-tuned on tuples of \((x, y)\). This is our simplest baseline.

**Rationale model.** We use the rationale model of Lei et al. (2016) for both supervised and unsupervised rationale generation. This model consists of two components (BERT modules in this case): a rationale extractor \(g\) that generates a binary attention mask \(\hat{\alpha}\) as the rationale, and a predictor \(f\) which makes a prediction using the rationalized input via a masking function \(m\) on \(x\) and \(\hat{\alpha}\) (Fig. 3):

\[
g(x) \rightarrow \hat{\alpha}, \\
f(m(x, \hat{\alpha})) \rightarrow \hat{y}.
\]

The two components are trained in tandem. In the unsupervised scenario, the joint objective function consists of a prediction loss term and a rationale sparsity term, encouraging the model to retain only those tokens in \(x\) that are necessary for accurate prediction:

\[
L_u = L_p(y, \hat{y}) + \lambda_{sp} \Vert \hat{\alpha} \Vert,
\]

where \(\lambda_{sp}\) is typically cross entropy.

In the supervised scenario, given a human rationale \(\alpha\), we replace the sparsity objective with a rationale supervision objective:

\[
L_{su} = L_p(y, \hat{y}) + \frac{\lambda_{su}}{L} \sum_{i=1}^{L} L_p(\alpha_i, \hat{\alpha}_i),
\]

where \(\lambda_{su}\) is a hyperparameter that controls the weight of rationale loss compared to label loss.

Each of these scenarios represents a baseline for our experiment. We refer to the unsupervised version as unsupervised rationale model, and the supervised version as supervised rationale model.

**Implementation details.** The original model of Lei et al. (2016) generates binary rationales by sampling from the Bernoulli distribution derived from the generator and uses the REINFORCE algorithm (Williams, 1992) to propagate approximate gradients through this non-differentiable operation.

We instead use Gumbel Softmax (Jang et al., 2017) to approximate binary rationale masks while still allowing for direct gradient descent. In this framework, the generator produces logits \(z_i\) to which are added random noise \(G \sim \text{Gumbel}(0, 1)\), before applying a softmax to produce class probabilities \(c_i\). This approximates a discrete distribution parameterized by \(e^{z_i}\). We then use the positive class probability \(c_i^1\) as the rationale value \(\alpha_i\).

\[
c_i = \text{softmax}(z_i + G \sim \text{Gumbel}(0, 1)); \hat{\alpha}_i = c_i^1
\]

Additionally, we find it helpful as an engineering trick to pre-train the predictive layer of this model on the full input. This step appears to mitigate some of the issues this model has with mode collapse, noted for example by DeYoung et al. (2019).

Given \(\hat{\alpha}_i\), we mask non-rationale tokens by multiplicatively substituting the [MASK] token vector across their vector representations, analogously to what is done during the MASK-LM pretraining of the BERT model:

\[
m_s(x_i, \hat{\alpha}_i) = \hat{\alpha}_i \cdot e_i + (1 - \hat{\alpha}_i) \cdot e_{\text{[MASK]}},
\]

where \(e_i\) represents the embedding associated with \(x_i\) and \(e_{\text{[MASK]}}\) is the embedding for the [MASK] token. We never mask special tokens [CLS] or [SEP], and we set \(\hat{\alpha}_i = 1\) for the query in MultiRC and FEVER as well because the query is always part of human rationales in these two datasets.

5.2 Learning from Human Rationales

Inspired by the analysis in §4, we propose four strategies for improving the efficacy of learning from rationales: 1) tuning class weights for rationale supervision; 2) enforcing sentence-level rationalization; 3) using “importance embeddings”; and...
4) selectively supervising only rationales with high sufficiency-accuracy. The first three are driven by the observed importance of rationale recall, while the last one is about human rationale quality.

**Class weights**. Rationales may become more effective enablers of overall model accuracy at different balances of precision and recall. We can adjust this balance simply by using differing weights to positive and negative values in rationale supervision:

$$\mathcal{L}_w = \mathcal{L}_p(y, \hat{y}) + \frac{1}{L} \sum_{i=1}^{L} (1 + \lambda_{su} \alpha_i) \mathcal{L}_p(\alpha_i, \hat{\alpha}_i),$$

where $\lambda_{su}$ controls the relative weight of rationale vs. non-rationale tokens. In particular, as we discuss in §4, we find that increased recall is associated with increased model accuracy. Thus, we explore several values for $\lambda_{su}$ in our experiment to encourage higher recall.

**Sentence-level rationalization**. Neither divergence from strict token-wise accuracy is to rationalize at the sentence rather than the token level. Given a function $\text{sent}$ mapping a token $x_i$ to its corresponding sentence $s$ consisting of tokens $\{\ldots, x_i, \ldots\}$, we use the average token-level logits $z_i$ in a sentence to produce a binary mask at the sentence level and then propagate that mask to all sentence tokens:

$$\hat{\alpha}_i = \hat{\alpha}_i^{\text{sent}(i)},$$

where $z^s = \frac{1}{|\{i | \text{sent}(i) = s\}|} \sum_{i | \text{sent}(i) = s} z_i$ is used to generate $\hat{\alpha}_i^{\text{sent}(i)}$.

**Importance embeddings**. Finally, a way to mitigate the impact of false negatives in predicted rationales is for these negatives to still remain visible to the predictor. This variant uses additive embeddings for rationalization rather than occluding masks, using a two-element embedding layer $e$ constituting one embedding for rationale tokens and one for nonrationale tokens. These embeddings are added to input tokens as specified by the binary output of the generator. This way, input tokens are tagged as important or unimportant, but the predictor $f$ has the freedom to learn how to engage with these tags for maximum label accuracy, rather than being fully blinded to “unimportant” tokens.

$$m_w(x, \hat{\alpha}) = e_i + (1 - \hat{\alpha}_i) e_{\text{non-rationale}} + \hat{\alpha}_i e_{\text{rationale}}.$$

An important drawback of this approach is that the predictor now has access to the full input instead of only the rationalized input, so these rationales provide a weak guarantee that important tokens are actually used to make predictions. This method also represents a large distribution shift from full text, so we find it necessary to calibrate the predictor using human rationales, as described in Fig. 1b. **Selective supervision**. Our fourth proposed method attempts to improve rationale prediction performance on high-sufficiency-accuracy rationales by selectively supervising only on human rationales with this property, ignoring those where human rationales do not allow a correct prediction.

Specifically, for every training batch, we use the true human rationales $\alpha$ as an input mask for the BERT predictor to get the HSA for each document. HSA then serves as a weight on the human rationale supervision during the main training batch:

$$\mathcal{L}_{w} = \mathcal{L}_p(y, \hat{y}) + \left(1 + f(m(x, \alpha))\right) \lambda_{su} \sum_{i=1}^{L} \mathcal{L}_p(\alpha_i, \hat{\alpha}_i).$$

### 6 Results

We start by introducing our experiment setup and then compare our proposed methods with baselines.

#### 6.1 Experiment Setup

Our goal in this experiment is to understand the impact of our four proposed learning methods. We do this with a comprehensive scan: We try three positive rationale supervision class weights $\lambda_{su} \in \{0, 2, 4\}$, and toggle sentence-level rationalization, importance embedding, selective supervision on and off. In addition, we vary rationale loss weight $\lambda_{su}$ in $\{0.5, 1, 2\}$. This resulted in 72 models for MultiRC and FEVER, and 36 models for E-SNLI (for which sentence-level rationalization is inappropriate because of the short snippets).

The best resultant model is our best overall model. The best model with $\lambda_{su} = 1$ (i.e., identical class weights for human rationales) and no other learning strategy enabled is our baseline supervised rationale model. We additionally train three unsupervised rationale models with sparsity weights 0.15, 0.25, and 0.35, selecting as representative the one which produced the sparsest rationales while maintaining a reasonable level of accuracy.

To evaluate the performance of our models, we consider both accuracy of the predicted labels ($\hat{y}$) and performance of rationale prediction in terms of F1, precision, and recall. We use Pytorch Lightning (Falcon et al., 2019) for training with a learning rate of $2e-5$ and gradient accumulation over 10 batches for all models. Early stopping was based on validation set loss with a patience of 3, evaluated every fifth of an epoch. Training was performed on two 24G NVidia TITAN RTX GPUs.
Table 2: Best-performing model variant compared to baseline models.

| Dataset   | Model                                   | F1     | Prec. | Rec.  | Masking | Granularity | Pos. class weight | Selective supervision |
|-----------|-----------------------------------------|--------|-------|-------|---------|--------------|--------------------|-----------------------|
| MultiRC   | BERT baseline                           | 68.1   | -     | -     | 73.9    | [MASK] Tokens | -                  | -                     |
|           | Unsupervised rationale model            | 67.2   | 22.2  | 18.5  | 27.9    | [MASK] Tokens | -                  | -                     |
|           | Supervised rationale model              | 67.0   | 46.5  | 41.5  | 52.9    | [MASK] Tokens | 1.0                | No                    |
|           | Best overall model                      | 71.2   | 57.1  | 44.9  | 78.4    | Embeddings Sentences | 5.0                | No                    |
| FEVER     | BERT baseline                           | 90.2   | -     | -     | 89.4    | [MASK] Tokens | -                  | -                     |
|           | Unsupervised rationale model            | 88.3   | 22.6  | 20.5  | 25.1    | [MASK] Tokens | -                  | -                     |
|           | Supervised rationale model              | 90.7   | 68.4  | 61.7  | 76.7    | [MASK] Tokens | 1.0                | No                    |
|           | Best overall model                      | 91.5   | 81.2  | 83.5  | 79.1    | 91.6 Embeddings Sentences | 1.0                | No                    |
| E-SNLI    | BERT baseline                           | 89.7   | -     | -     | 73.9    | [MASK] Tokens | -                  | -                     |
|           | Unsupervised rationale model            | 88.9   | 40.6  | 28.2  | 72.6    | [MASK] Tokens | -                  | -                     |
|           | Supervised rationale model              | 87.8   | 58.7  | 47.2  | 76.0    | [MASK] Tokens | 1.0                | No                    |
|           | Best overall model                      | 90.1   | 59.6  | 45.5  | 86.2    | 92.3 Embeddings Tokens | 3.0                | No                    |

Table 3: Regression coefficients for effect each proposed method on overall prediction accuracy.

| Method       | Coefficients                  | MultiRC | FEVER | E-SNLI |
|--------------|------------------------------|---------|-------|--------|
|             | Sentences                     | .015*** | .001  | -      |
| Class weights| Class weights                 | .017*** | .007***| .005   |
| Embeddings   | Embeddings                    | .012*** | .006***| -.010**|
| Selective supervision | Selective supervision | .004    | - .006***| -.032***|

Table 4: Label accuracy and predicted rationale F1 for high- versus low-HSA examples.

6.2 Model Performance

Table 2 compares our best overall model against the baselines, and presents the learning strategies used in the models.

Label accuracy. For MultiRC, this best model includes every proposed intervention (sentence-level rationalization, importance embeddings, class weights) except for selective supervision, and yields a 3-point improvement from the baseline accuracy of 68.1% to 71.2%. We observe a more modest improvement on FEVER, with the best model using sentence-level rationalization and importance embeddings, and scoring a 1-point improvement from 90.2% to 91.5%. We note, however, that this approaches the accuracy of the model with access to a human rationale oracle (91.6%). Finally, we observe a tiny improvement of 0.4% on E-SNLI, though our proposed methods do improve upon the baselines of unsupervised and supervised rationale model, which causes a performance drop.

A McNemar’s significance test with Bonferroni correction between the best and baseline model finds that the accuracy improvement is significant for MultiRC and FEVER (\(p = 2e-7\) and 3e-6 respectively) and not significant for E-SNLI (\(p = 0.1\)). The limited improvement in E-SNLI echoes the performance drop in Fig. 1a without adaptation, suggesting that human rationales in this dataset are too idiosyncratic to improve model performance.

Factor analysis. We use regression analysis to understand the impact of the different modifications on model accuracy. Table 3 suggests that rationale class weighting has the highest positive effect on accuracy across datasets. Importance embeddings have a positive effect for MultiRC and FEVER and a negative effect for E-SNLI, while sentence-level rationalization improves only MultiRC.

Selective supervision is found to have a non-existent or negative effect across all three datasets. Table 4 details this result, showing model accuracy and rationale performance for the best model with (yes) vs. without (no) selective supervision. If our method succeeded, F1 for high-HSA examples would increase from the “No” to the “Yes” models and remain flat or decrease for low-HSA examples. Indeed, we observe lower rationale F1 for low-HSA examples, but the rationale F1 also drops substantially for high-HSA examples, possibly because of the reduced available training data.

A potential solution may be selective application rather than selective supervision, where the model learns to predict both the rationale and its sufficiency-accuracy, then selectively applies it as a mask on the input. We leave this for future work.

Rationale performance. Although our strategies are designed to improve recall of human rationales, they also improve prediction and F1 in most cases. The only exception is the reduced precision in E-SNLI compared to the supervised rationale model.
6.3 Qualitative Analysis

Table 5 shows two examples drawn from MultiRC to further illustrate our results. For each example, we show the human rationale and predicted rationales for both the supervised rationale model and our best overall model. We present the ground truth label, alongside the model predictions and the human-rationalyzed prediction for that model.

Example 5A shows an instance where our model more successfully captured the (sufficient) information present in the human rationale, allowing for a correct prediction where the supervised rationale fails. This example illustrates the role of sentence-level tokenization and class weights in encouraging recall in human rationales.

Example 5B presents an interesting contrast. In this case, the human rationale does not include “making pictures of flowers” and has insufficient information for prediction, tricking both models when they make predictions on the human-rationalyzed input. This observation echoes Fig. 1a with respect to “good” and “bad” human rationales. Fortunately, both models were able to correctly identify the relevant portions of the text in their own rationales and make the correct classification.

7 Discussion

An idiosyncrasy of our analysis is that all three datasets are document-query style reading comprehension tasks, as opposed to e.g. sentiment analysis. One difference between the two tasks is that human rationales for sentiment are likely to contain more redundant signal, which could impact their sufficiency-accuracy and potential utility as signal. We leave a more comprehensive survey of available rationale datasets for future work.

Nevertheless, by examining model performance with oracle access to human rationales, the analysis in section §4 establishes a limit of potential improvement from learning from rationales. It suggests two basic insights toward improved learning from rationales: 1) that insofar as they boost model performance, not all human rationale tokens are equally valuable, with e.g. false positives causing less degradation than false negatives; and 2) that in theory, we could boost performance further with good accuracy on useful (high-SA) rationales and low accuracy on useless (low-SA) ones.

We exploit these two insights with four modifications to the baseline architecture. Three of these pursue improved recall: rationale supervision class weighting, sentence-level rationalization, importance embeddings; and one, selective supervision, pursues utility-discriminative accuracy.

Altogether, our proposed methods yield a substantial 3% improvement over baseline performance for MultiRC, a 1% improvement on FEVER, and a tiny .4% improvement on E-SNLI, mirroring the potential improvements observed in the analysis. We find that all three recall-boosting methods are useful in achieving this, while selective supervision has a marginal or negative effect.

In summary, our results support the potential for learning from rationales in certain datasets, and demonstrate the importance of understanding the properties of human rationales to properly exploit them for this purpose. We believe that these two insights are useful steps towards effective learning from rationales, and could yield even greater improvements if operationalized optimally.
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A Detailed Factor Analysis

Table 6 compares, for each proposed method, the performance of the best model using that method and the best model not using it. The story shown here is similar to the regression analysis in Table 3, but one new insight is that the improvement in model prediction performance appears to be driven by the sentence-level rationalization method, as it cuts down on stray tokens dropped from or added to the predicted rationales.

B Rationale Perturbation on FEVER and E-SNLI

Furthering the analysis in §4.2, we extend the human rationale perturbation experiment to FEVER and E-SNLI.

Fig. 4 show the result for FEVER. Fig. 4a shows that the baseline accuracy is so high for this dataset that to match just the baseline accuracy for FEVER, we require near perfect prediction of human rationales.

Moreover, even for documents with HSA = 1, the model performance drops below baseline on dropping just ∼10% tokens (synonymous with rationale recall = ∼0.9) in Fig. 4b. Interestingly, the model performance remains consistently above the baseline when adding non-rationale tokens (synonymous with decreasing rationale precision). In comparison, the model performance for MultiRC in Fig. 2b drops below baseline after dropping ∼50% of the tokens.

For FEVER examples with HSA = 0 (Fig. 4c), the model performance remains below the baseline accuracy consistently, supporting the second hypothesis in §4.2. The near-perfect need to predict rationales in FEVER may explain behind the difference in improvements of model performance between MultiRC and FEVER.

Fig. 5 covers E-SNLI. We see that the model performance decreases after dropping rationale tokens (signifying decreasing recall) and it consistently remains below the baseline. In contrast, the model performance shows a slight improvement after adding non-rationale tokens (signifying decrease in rationale precision). Moreover, for documents with HSA = 1, the model performance drops below baseline at ∼3% for dropping and swapping rationale tokens, where as the model performance plateaus with addition of non-rationale tokens. These insights highlights the substantial challenges in learning from explanations for E-SNLI.

C Rationale Perturbation for Adapted Models

We perform the same perturbation analysis on calibrated model trained on both full and rationalized input, for which distribution shift from masking are less of a concern.

In Fig. 6, for MultiRC, we find that model performance plateaus with addition of non-rationale tokens and drops quickly with rationale tokens even for a calibrated model. This observation is consistent for FEVER (Fig. 7).

For E-SNLI, we find different properties using a calibrated BERT model compared to the standard BERT model show in Fig. 5a.

In contrast to MultiRC and FEVER, we find that the model performance drops more rapidly with the addition of non-rationale tokens compared to removal of rationale tokens. This is consistent for documents with HSA = 1, suggesting that for E-SNLI, rationale precision maybe more important when using a calibrated model. Similar to FEVER, we see the model performance drop below the baseline with very little corruption of rationales, echoing the need to perfectly mimic human rationalization for effective learning from rationales for this dataset.
| Dataset | Method | Role | Accuracy | Rationale prediction | Human Suff. Acc. |
|---------|--------|------|----------|---------------------|-----------------|
|         |        |      |          | F1 | Precision | Recall |
|         |        |      |          |     |           |       |
|         |        |      |          |     |           |       |
|         |        |      |          |     |           |       |
|         |        |      |          |     |           |       |
|         |        |      |          |     |           |       |
| Sentences | Best with | 71.2 | 57.1 | 44.9 | 78.4 | 74.5 |
| Sentences | Best without | 70.6 | 41.6 | 27.7 | 84.1 | 75.8 |
| MultiRC | Class-weights | Best with | 71.2 | 57.1 | 44.9 | 78.4 | 74.5 |
|         | Class-weights | Best without | 70.8 | 55.2 | 66.1 | 47.4 | 76.5 |
|         | Importance embeddings | Best with | 71.2 | 57.1 | 44.9 | 78.4 | 74.5 |
|         | Importance embeddings | Best without | 71.0 | 53.6 | 39.7 | 82.5 | 75.8 |
|         | Selective supervision | Best with | 71.0 | 53.6 | 39.7 | 82.5 | 75.8 |
|         | Selective supervision | Best without | 71.2 | 57.1 | 44.9 | 78.4 | 74.5 |
| Sentences | Best with | 91.5 | 81.2 | 83.5 | 79.1 | 91.6 |
| Sentences | Best without | 91.3 | 72.4 | 61.3 | 88.5 | 91.6 |
| FEVER | Class-weights | Best with | 91.5 | 79.6 | 73.1 | 87.3 | 91.8 |
|         | Class-weights | Best without | 91.5 | 81.2 | 83.5 | 79.1 | 91.6 |
|         | Importance embeddings | Best with | 91.5 | 81.2 | 83.5 | 79.1 | 91.6 |
|         | Importance embeddings | Best without | 91.4 | 80.0 | 74.9 | 85.9 | 91.8 |
|         | Selective supervision | Best with | 90.6 | 56.4 | 41.4 | 88.6 | 90.4 |
|         | Selective supervision | Best without | 91.5 | 81.2 | 83.5 | 79.1 | 91.6 |
|         | Class-weights | Best with | 90.1 | 59.6 | 45.5 | 86.2 | 92.3 |
|         | Class-weights | Best without | 89.9 | 62.2 | 55.7 | 70.4 | 92.0 |
| E-SNLI | Importance embeddings | Best with | 90.1 | 59.6 | 45.5 | 86.2 | 92.3 |
|         | Importance embeddings | Best without | 89.9 | 33.5 | 20.2 | 100.0 | 72.5 |
|         | Selective supervision | Best with | 88.8 | 49.0 | 33.2 | 93.4 | 84.0 |
|         | Selective supervision | Best without | 90.1 | 59.6 | 45.5 | 86.2 | 92.3 |

Table 6: Comparison of best model with each proposed factor against best model without that factor.

Figure 4: Performance of corrupted rationale for FEVER. Model performance drops below baseline accuracy immediately on both dropping human rationales (i.e., recall ↓) and adding non-rationale tokens (i.e., precision ↓). For HSA = 1, model performance remains consistently above baseline on adding non-rationale tokens (i.e. precision ↓)

Figure 5: Performance of corrupted rationales for E-SNLI. Model performance for human rationale remains below baseline accuracy and slightly increases with addition of non-rationale tokens (i.e. precision ↓). Even for HSA = 1, model performance drops below baseline accuracy at just ~4% corruption.
Figure 6: Performance of corrupted rationales for MultiRC using a calibrated model. Model performance decreases consistently when we drop human rationales (i.e., recall ↓), whereas the model performance stays high as we add non-rationale tokens (i.e., precision ↓). The impact of recall is moderated when HSA = 1.

Figure 7: Performance of corrupted rationales for FEVER using a calibrated model. Model performance decreases quickly when we drop human rationales (i.e., recall ↓), whereas the model performance remains above baseline as we add non-rationale tokens (i.e., precision ↓).

Figure 8: Performance of corrupted rationales for E-SNLI using a calibrated model. Model performance decreases quickly when we add non-rationale tokens (i.e., precision ↓), whereas the model performance drops less rapidly as we drop rationale tokens (i.e., recall ↓).