The Unreliability of Explanations in Few-Shot In-Context Learning

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Abstract

How can prompting a large language model like GPT-3 with explanations improve in-context learning? We focus specifically on two NLP tasks that involve reasoning over text, namely question answering and natural language inference. Including explanations in the prompt and having the model generate them does not consistently improve performance in the settings we study, contrary to recent results on symbolic reasoning tasks (Nye et al., 2021; Wei et al., 2022). Despite careful prompting, explanations generated by GPT-3 may not even be factually grounded in the input, even on simple tasks with straightforward extractive explanations. However, these flawed explanations can still be useful as a way to verify GPT-3’s predictions post-hoc. Through analysis in three settings, we show that explanations judged as good by humans—those that are logically consistent with the input and the prediction—usually indicate more accurate predictions. Following these observations, we present a framework for calibrating model predictions based on the reliability of the explanations. Our framework trains calibrators using automatically extracted scores that approximately assess the reliability of explanations, which helps improve performance across three different datasets.

Figure 1: Prompting GPT-3 with explanations. By including explanations in the in-context examples, we can cause GPT-3 to generate an explanation for the test example as well. In this case, the generated explanation is nonfactual, despite the simple reasoning involved here. However, we show this nonfactualy actually provides a signal that can help calibrate the model.
1 Introduction

Recent breakthroughs in pre-training have empowered large language models to learn from just a few examples. In-context learning, learning a new task from training examples in a prompt without updating parameters, has shown promising performance for very large language models like GPT-3 (Brown et al., 2020). However, this learning process is still poorly understood: models are biased by the order of examples they are shown (Zhao et al., 2021) and may not leverage the instructions or even the labels of the few-shot examples in the ways we expect (Min et al., 2022; Webson and Pavlick, 2022). It is difficult to investigate these issues or explain the predictions of in-context learning when existing tools for interpreting model predictions have high computational cost (Ribeiro et al., 2016) or require access to gradients (Simonyan et al., 2014; Sundararajan et al., 2017).

One appealing way to gain more insight into predictions obtained through in-context learning is to let the language model “explain itself” (Nye et al., 2021; Wei et al., 2022; Chowdhery et al., 2022; Marasović et al., 2022; Lampinen et al., 2022). In addition to input-label pairs, one can prompt the language model with explanations for input-label pairs and expect the model to generate an explanation corresponding to the prediction it gives (Figure 1). Prompting with explanations introduces much richer information compared to using labels alone, which might guide the in-context learning process and allow the model to leverage more information about the examples.

In this work, we closely investigate the nature of the explanations that GPT-3 generates and whether they can really improve few-shot in-context learning, specifically for textual reasoning tasks. Recent prior work that finds success with this approach largely targets symbolic reasoning tasks with a very different structure, such as math word problem solving (Nye et al., 2021; Wei et al., 2022). We show that explanations do not always improve performance when plugged into the prompt (Figure 1) across three different datasets spanning QA and NLI.

Surprisingly, we find that the explanations generated by GPT-3 are unreliable, in addition to not boosting the performance. Specifically, we check the explanations along two axes: factuality, whether the explanation is correctly grounded in the input, and consistency, whether the explanation entails the final prediction. As shown in Figure 1, GPT-3 tends to generate consistent explanations that account for the predictions, but the explanations may not faithfully be grounded in the context in the inputs, even for a very simple synthetic dataset. Furthermore, our analysis suggests a nonfactual explanation more likely indicates a wrong prediction, compared to a factual explanation.

Despite GPT-3’s failures here, we can still benefit from model-generated explanations by using them for calibration, given the connection between nonfactual explanations and incorrect predictions. If we are able to automatically assess the factuality of an explanation, we can allow GPT-3 to return a null answer when its explanation is unreliable. Unfortunately, there is no automated way to perfectly assess the factuality, but we can extract features that approximately reflect it. We use these features to calibrate GPT-3’s predictions, and successfully improve the in-context learning performance across all the datasets.

In summary, our main findings are:

- Simply plugging explanations into the prompt does not necessarily improve the in-context learning performance for textual reasoning tasks.
- GPT-3 can generate mostly consistent explanations, but these explanations might not be faithfully grounded in the inputs.
- The factuality of an explanation can serve as an indicator for the correctness of the corresponding prediction.
- Using features that can approximate the factuality of explanations, we successfully use explanations to improve the in-context learning performance across all tasks.

2 Does Prompting with Explanations Improve In-Context Learning?

In this paper we specifically focus on tasks involving reasoning over natural language. These are tasks where explanations have been traditionally studied (Camburu et al., 2018; Rajani et al., 2019), but which are more complex than tasks like sentiment which are well explained by extractive rationales (Zaidan et al., 2007; DeYoung et al., 2020). We experiment on two tasks, reading comprehension
Christopher agrees with Kevin. Tiffany agrees with Matthew. Mary hangs out with Danielle. James hangs out with Thomas. Kevin is a student. Matthew is a plumber. Danielle is a student. Thomas is a plumber.

Who hangs out with a student?

Mary

Mary hangs out with Danielle. Danielle is a student.

A toddler in a green and yellow jersey is being followed by a wheelchair bound woman in a red sweater past a wooden bench.

A toddler is walking near his wheelchair bound grandmother.

Neither

the woman may not be his grandmother.

E-SNLI is a classification dataset that is commonly for the purpose of studying the usage of explanations. Shown in Figure 2, each example consists of a premise and a hypothesis, and the task is to classify the hypothesis as entailed by, contradicted by, or neutral with respect to the premise. As a notable contrast to the other datasets, the explanations here are more abstract natural language written by human annotators, as opposed to mostly constructed from extracted snippets of context.

2.1 Datasets

Synthetic Multi-hop QA (SYNTHETIC) In order to have a controlled setting where we completely understand whether explanations are factual and consistent with the answer, we create a synthetic multi-hop QA dataset. As shown in Figure 2, each example in our synthetic dataset asks a bridge question (using the terminology of Yang et al. (2018)) over a context consisting of supporting facts paired with controlled distractors. This dataset is carefully designed to avoid spurious correlations, giving us full understanding over the correct reasoning process as well as the explanation for every example, which naturally consists of the two supporting sentences. Refer to Appendix B for full details of this dataset.

Adversarial HotpotQA (ADVHOTPOT) We also test on the Adversarial HotpotQA dataset (Yang et al., 2018; Jiang and Bansal, 2019). We opt to use the adversarially augmented version since GPT-3 achieves high performance on the distractor setting of the original dataset. We make a challenging set of examples by balancing sets of questions on which GPT-3 makes correct and incorrect predictions. The context of each question includes two ground truth supporting paragraphs and two adversarial paragraphs. Full details of preprocessing the ADVHOTPOT dataset can be found in Appendix C.

For ADVHOTPOT, we manually annotated explanations for the training examples. Figure 1 shows an example of this explanation, highlighted in orange. We could use the supporting sentences as the explanations, but we found they are usually too verbose and not sufficient, e.g., with anaphors that resolve outside of the supporting sentences. Therefore, we manually annotate a set of explanations which clearly describes the reasoning path for the question.

E-SNLI E-SNLI is a classification dataset that is commonly for the purpose of studying the usage of explanations. Shown in Figure 2, each example consists of a premise and a hypothesis, and the task is to classify the hypothesis as entailed by, contradicted by, or neutral with respect to the premise. As a notable contrast to the other datasets, the explanations here are more abstract natural language written by human annotators, as opposed to mostly constructed from extracted snippets of context.

2.2 Baselines

We study the effectiveness of plugging in explanations by comparing the in-context learning performance of prompting with or without explanations. Prompting without explanations resembles the standard few-shot in-context learning approach (Few-Shot). To incorporate explanations into the prompt, we consider the following two most commonly used paradigms:

Explain-then-Predict (E-P) which prepends an explanation before the label (Figure 1). The language model is expected to generate an explanation first followed by the prediction. The prompting style of

1This dataset is inspired by the bAbI dataset (Weston et al., 2016). In our preliminary experiments with some of the more complex bAbI tasks, we found poor performance from GPT-3 similar to our results on SYNTHETIC, both with and without explanations.
Table 1: Comparison between the in-context learning performance without and with explanations. Using explanations does not consistently improve performance.

|                  | SYNTHETIC | ADVHOTPOT | E-SNLI   |
|------------------|-----------|-----------|----------|
| few-shot         | 54.8 ± 2.5| 53.2 ± 2.3| 56.8 ± 2.0|
| E-P              | 50.6 ± 1.6| 58.2 ± 4.1| 41.8 ± 2.5|
| P-E              | 53.3 ± 1.6| 51.5 ± 2.4| 59.4 ± 2.0|

Past work involving computational traces can be categorized into this paradigm, including [Nye et al. (2021)] and [Wei et al. (2022)]. It is also called a pipeline model in other literature on training models using explanations [Jacovi and Goldberg, 2021; Wiegreffe et al., 2021].

**Predict-then-Explain (P-E)** which first gives a prediction and then generates the explanation. Unlike E-P, the predicted explanation does not influence the predicted label, since we use greedy inference and the explanation comes afterwards. However, the explanations in the prompt itself still impact the model’s behavior.

### 2.3 Setup

For few-shot learning, we use roughly the maximum allowed shots in the prompt that can fit the length limit of GPT-3, which is 16 for SYNTHETIC, 6 for ADVHOTPOT, and 32 for E-SNLI, respectively.

Because the results of in-context learning vary with the examples presented in the input prompt, for each dataset, we randomly sample 5 groups of training shots, and report the mean and standard deviation of the results.

All our experiments use the 175B GPT-3 [Brown et al., 2020] Instruct series API (text-davinci-01), the strongest available model at the time of our experiments. The completion is obtained through greedy decoding (temperature set to be 0). Our prompt formats follow those in [Brown et al., 2020]. The explanations are inserted before/after the prediction with conjunction words like *because*. Please refer to Appendix A for full prompts.

### 2.4 Results

As shown in Table 1, we do not see strong performance improvement from adding explanations. In particular, introducing explanations leads to moderate performance degradation on SYNTHETIC. On ADVHOTPOT and E-SNLI, using explanations does improve the performance from 53.8 to 58.2 and from 56.8% to 59.4%, respectively, but the two datasets benefit from different methods. Prepending explanations before the predictions (E-P) outperforms P-E on ADVHOTPOT, but substantially lags P-E on E-SNLI. There is no single winner between the two paradigms; choosing the most effective way of plugging in explanations is task-specific.

Our results do not suggest immediate strong improvements from incorporating explanations, contradicting recent prior work. This can be attributed to the difference between the tasks we study. The tasks that receive significant benefits from using explanations in [Nye et al., 2021] and [Wei et al., 2022] are all program-like (e.g., integer addition and program execution), whereas the tasks in this work emphasize textual reasoning grounded in provided inputs. In fact, in [Wei et al., 2022] and [Chowdhery et al., 2022], explanations only show mild benefit on open-domain QA tasks like StrategyQA [Geva et al., 2021] that are closer to our setting.

### 3 Can GPT-3 Generate Factual and Consistent Explanations?

Prompting GPT-3 with explanations and generating explanations does not lead to much higher prediction accuracy on our tasks here. But what about the quality of the model-generated explanations? This contrasts with recent work like [Zhao et al., 2021] that focuses on improving performance in the 1-4-shot setting; by using more data we achieve much stronger results on our tasks.
### Table 2: Left: factuality and consistency of the generated explanations across different datasets. Right: the % of the examples whose explanation factuality is congruent with the prediction accuracy. In general, GPT-3 tends to generate consistent but less likely factual explanations.

|                      | Accuracy | Factuality | Consistency | Accuracy = Factuality |
|----------------------|----------|------------|-------------|-----------------------|
| SYNTHETIC (P-E)      | 51.2     | 52.8       | 100.        |                       |
| ADVHOTPOT (E-P)      | 62.0     | 79.6       | 91.2        | 80.0                  |
| E-SNLI (P-E)         | 62.0     | –          | 98.8        | –                     |

Figure 3: Explanations generated for ADVHOTPOT. GPT-3 may generate nonfactual explanations containing hallucination or inconsistent explanations contradicting the answer. Contradicting parts are highlighted.

For SYNTHETIC, we can construct rules to automatically judge whether an explanation is factual and consistent. For ADVHOTPOT and E-SNLI, the authors manually inspected the explanations and annotated them for these two characteristics. Note for each setting, the results are based on the explanations and predictions obtained with a single set of training shots. For each dataset, we annotate the explanations generated by whichever is the best paradigm between E-P and P-E. We have also assessed the reliability for E-P on SYNTHETIC and P-E on ADVHOTPOT in Appendix D.

#### Results

We summarize the results in Table 2. We only report consistency on E-SNLI, as the explanations for E-NLI often require some external commonsense knowledge which cannot be easily grounded in the inputs or judged as true or false (examples in Appendix F). Overall, GPT-3 tends to generate consistent explanations, but the explanations are less likely to be factual. The factuality rate is 51.2% on SYNTHETIC and 79.6% on ADVHOTPOT, far lagging the consistency rates of 100% and 91.2%. In particular, the explanations almost always entail the predictions on SYNTHETIC and E-SNLI.

### 3.1 Reliability of Explanations and Prediction Accuracy

GPT-3 may hallucinate problematic explanations, but this could actually be advantageous if it gives us a way of spotting when the model’s “reasoning” has failed. We investigate the connection
between the reliability of an explanation and the accuracy of a prediction, and ask whether a reliable explanation indicates an accurate prediction.\footnote{This use of explanations bears some resemblance to the linguistic calibration of Mielke et al. (2020), which tries to align certainty indicators in dialogue agent responses with expected correctness. However, they find this verbalized confidence is poorly calibrated.}

As shown in the right section of Table 2, we see that accuracy and factuality are highly correlated: by knowing whether an explanation is factual, we can guess the model’s prediction a high fraction of the time (Accuracy = Factuality). A nonfactual explanation almost always (98.4%) means an incorrect prediction on the SYNTHETIC dataset. On ADVHOTPOT, the accuracy against the model’s prediction reaches 80.0%, substantially surpassing the prediction accuracy itself.

We show fractions of correct predictions and incorrect predictions when the explanations are factual/nonfactual and consistent/inconsistent in Figure 4. Factual explanations are much more likely paired with correct predictions compared to nonfactual explanations. Consistency also connects to the accuracy on ADVHOTPOT, but is an inferior indicator compared to factuality.

4 Calibrating In-Context Learning using Explanations

From the previous section, we see that a human oracle assessment of the factuality of an explanation could be of substantial use for calibrating the corresponding prediction. Can we automate this process?

We show how to achieve this goal on the perfectly controlled SYNTHETIC dataset (Section 4.1). On our other two datasets, we use surface lexical matching to approximate semantic matching and give real-valued scores approximately reflecting factuality. Following past work on supervised calibration (Kamath et al., 2020; Chen et al., 2021; Ye and Durrett, 2022), we can learn a calibrator that tunes the probabilities of a prediction based on the score of its explanation (Section 4.2). We show such a calibrator can be trained with a handful of examples beyond those used for in-context learning and successfully improve the in-context learning performance on realistic datasets.\footnote{This procedure does require extra data. However, it provides a natural avenue for using a small number of additional examples that otherwise would be impossible to incorporate into this procedure, when the size of the context actually limits the amount of data for in-context learning.}

4.1 Motivating Example: Improving SYNTHETIC Dataset

We first show how post-hoc calibration functions in the controlled SYNTHETIC setting, where we can simply check the factuality of an explanation. Since the generated explanation always follow a certain a format “A [verb] B. B is [profession].” (example in Figure 2), we can split the explanation into two sentences. Then the explanation is factual if and only if both of the sentences exactly match one of the sentences in the context.

A nonfactual explanation almost always indicates an incorrect prediction on this dataset. This gives us a way to reject presumably incorrect answers. Specifically, we iterate through the top 5 candidate

Figure 4: Explanations are more likely to be nonfactual than to be inconsistent, and a nonfactual explanation usually indicate an incorrect prediction.
answers given by GPT-3 and reject any answer-explanation pair if the explanation is nonfactual until we find a factual one.

This procedure dramatically improves the accuracy from 54.8% to 84.2%. Note that this SYNTHETIC dataset without any possible reasoning shortcuts is a challenging task. For reference, neither RoBERTa [Liu et al., 2019] and DeBERTa [He et al., 2021] finetuned with 16 examples can achieve an accuracy surpassing 50%. With the help of the explanations and the checking procedure, we can use GPT-3 to achieve strong results using few-shot learning.

4.2 Learning-based Calibration Framework

Framework We now introduce the framework that can leverage the factuality assessment of an explanation to calibrate a prediction. Let \( p \) be the vector of predicted probabilities associated with each class label in NLI (or the probability score of predicted answer in QA). Let \( v \) be a scalar value extracted from the explanation to describe the factuality. Then, we can adjust the probabilities accordingly using a linear model:

\[
\hat{p} = \text{softmax}(W[p; v] + b),
\]

where \( \hat{p} \) is the tuned probabilities. Our calibration framework is extended from classical calibration methods (Platt, 1999; Guo et al., 2017; Zhao et al., 2021), which apply an affine transformation on the probabilities alone: \( \hat{p} = \text{softmax}(Wp + b) \). In contrast, we use an additional factor \( v \) in calibration to incorporate the factuality assessment of the explanation.

There are a small number of parameters (\( W \) and \( b \)) that need to be trained in such a calibration framework. We will rely on a few more examples in addition to the shots we use in the prompt to train the calibrator. Specifically, we use the prompt examples to generate the predictions and explanations for these extra examples, and extract predicted probabilities, factors, and target probabilities triples to construct training data points used to train the calibrator. Note this procedure requires no explanation annotations for the extra examples.

Approximating Factuality We approximate the factuality using lexical overlap between the explanations and the inputs, which we found to work fairly well for our tasks.

ADVHOTPOT: We use an explanation consisting of two sentences (examples in Figure 3) as an illustration. Let \( \mathcal{E} = (E^{(1)}, E^{(2)}) \) be the generated explanation, where \( E^{(1)} \) and \( E^{(2)} \) are the two sentences, and the \( E^{(i)} = (e_1, e_2, \cdots) \) contain tokens \( e_1, e_2, \cdots \). Similarly, let \( \mathcal{P} = (P^{(1)}, P^{(2)}, P^{(3)}, P^{(4)}) \) be the context paragraphs, and \( P^{(i)} = (p_1, p_2, \cdots) \) be the tokens. The factuality estimation of one explanation sentence \( E^{(i)} \) is defined as:

\[
\mathcal{V}(E^{(i)}) = \max_{P \in \mathcal{P}} \frac{|E^{(i)} \cap P|}{|E^{(i)}|}.
\]

Intuitively, the factuality score for a sentence \( E \) is defined as the maximum number of overlapping tokens over all paragraphs \( P \), normalized by the number of tokens in \( E \). We then define the factuality score for the whole explanation as:

\[
\mathcal{V}(\mathcal{E}) = \min_{E \in \mathcal{E}} \mathcal{V}(E),
\]

as it requires all sentences to be factual in order to make the entire explanation factual.

E-SNLI: On the E-SNLI dataset whose explanations do not really involve a concept of factuality, we still use an analogous score following the same principle, where we regard the premise as the context. Let \( E = (e_1, e_2, \cdots) \) be the explanation and \( P = (p_1, p_2, \cdots) \) be the premise. We simply score the explanation by \( \mathcal{V}(E) = \frac{|E \cap P|}{|E|} \). Namely, the more an explanation overlaps with the premise, the more factual it is.
Table 3: Accuracy of various methods on E-SNLI under different data conditions. L denotes number of labels (as well as the total number of examples); E denotes the number of explanations. Calibrating using explanations successfully improves the performance of in-context learning.

| Method                     | 32L   | 64L   | 96L   | 128L  |
|----------------------------|-------|-------|-------|-------|
| w/o Explanation            |       |       |       |       |
| RoBERTa                    | 40.1±4.7 | 43.0±5.1 | 49.0±5.2 | 54.9±4.8 |
| Few-Shot                   | 56.8±2.0   |       |       |       |
| Few-Shot(NN)               |       |       |       | 58.9±1.0 |
| Few-Shot+PROBCALIB         | 61.9±3.8   | 62.4±2.6 | 63.2±2.9 | 63.9±1.2 |
| w/ Explanation             | 64L+32E | 96L+32E | 128L+32E |       |
| P-E                        | 59.4±2.0   |       |       |       |
| P-E+PROBCALIB              | 64.4±1.8   | 65.4±1.2 | 65.4±1.6 | 65.4±1.9 |
| P-E+EXPLICALIB             | 64.2±2.6   | 65.8±1.3 | 67.6±1.6 | 68.5±1.2 |
| P-E+ZHANG ET AL. (2021)    |       | 65.2±2.2 | 65.4±1.5 | 65.9±2.5 |

4.3 Calibrating E-SNLI

Setup For E-SNLI, we use calibration methods to postprocess the final probabilities. Unlike classical temperature scaling (Platt, 1999), note that the methods we use here can actually change the prediction; we will therefore evaluate on accuracy of the calibrated model.

We study the effectiveness of our explanation-based calibrator under different training data sizes varying from 32 to 128. Recall that we only require explanation annotations for 32 data points, and only need the labels for the rest to train the calibrator. For E-SNLI, we calibrate P-E, which is shown to be more effective than E-P in this setting (Section 2.4).

Baselines To isolate the effectiveness of using explanations for calibration, we introduce three additional baselines using non-explanation-based calibrators. We apply the probability-based calibrator as described in Section 4.2 on the results obtained on few-shot learning ( Few-Shot+PROBCALIB) and predict-then-explain pipeline (P-E+PROBCALIB). We note that the parameters of these calibrators are trained using the addition data points, as opposed to being heuristically determined as in Zhao et al. (2021). Furthermore, we experiment with a recently proposed supervised calibrator from Zhang et al. (2021), which uses the CLS representations from an additional language model as features in the calibrator. The probabilities are tuned using \( \hat{p} = \text{softmax}(W[p; h] + b) \), where \( h \) is the CLS representation. Since we do not have access to the embeddings obtained by GPT-3, we use RoBERTa to extract the vectors instead. We use such a calibrator on top of our best-performing base model, P-E, resulting P-E+ZHANG ET AL. (2021).

Limited by the maximum prompt length, in-context learning is not able to take as input the additional data used for training the calibrator. For a fair comparison, we can allow the in-context model to use this data by varying the prompts across test examples, dynamically choosing the prompt examples to maximize performance. Choosing closer data points for prompting is a common and effective way of scaling up the training data size for in-context learning (Shin et al. 2021; Liu et al. 2021). Following Liu et al. (2021), we test the performance of choosing nearest neighbors for the prompt based on CLS embedding produced by a RoBERTa model (Liu et al. 2019), referred as Few-Shot(NN). It is worth clarifying that the Few-Shot and Few-Shot+PROBCALIB approaches use the same set of 32 training shots in the prompt for every test example, whereas the shot sets vary from example to example in Few-Shot(NN).

Lastly, we provide the performance of fine-tuned RoBERTa (Liu et al. 2019) model as a reference.

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6 Alternatively, one might use a fine-tuned NLI model as a proxy (Chen et al. 2021). However, our focus is on the pure black-box setting, and we avoid models that require substantial amounts of data to make work.

7 We also tried a more recent DeBERTa model (He et al. 2021), but found it to be worse than RoBERTa in the few-shot E-SNLI setting.
Table 4: AUC scores of various methods on ADVHOTPOT under different data conditions. L and E denote the number of label annotations and explanation annotations, respectively. Explanation-based calibration successfully improves the performance on top of using explanations in the prompt.

|                | 6L  | 32L | 64L |
|----------------|-----|-----|-----|
| w/o Explanation|     |     |     |
| Few-Shot       | 59.6±2.4 | –   | –   |
| Few-Shot(NN)   | –   | –   | 61.3±0.9 |
| w/ Explanation |     |     |     |
| E-P            | 64.4±2.9 | –   | –   |
| E-P+EXPLCALIB  | –   | 67.2±3.2 | 68.8±2.9 |
| E-P+ZHANG ET AL (2021) | – | 65.6±3.9 | 66.1±3.2 |

Results We show the results in Table 4. We use 5 different groups of training examples and report the mean and standard deviation across the groups. For Few-Shot(NN), we only report the results obtained using 128 examples.

Under 128 training examples, applying a trained calibrator on top of prompting with explanation (i.e., P-E+EXPLCALIB) achieves the best accuracy of 68.5%, which is 12% higher than the performance of the vanilla uncalibrated few-shot in-context learning (Few-Shot). P-E+EXPLCALIB also outperforms Few-Shot+ProbCALIB and P-E+ProbCALIB by 5% and 3%, respectively. Using explanations is more effective than using probabilities alone. In addition, P-E+EXPLCALIB also outperforms P-E+ZHANG ET AL (2021), whose performance is on par with P-E+ProbCALIB. This suggests the additional CLS information is not very helpful in this setting.

As the data size increases from 32 to 128, the performance of the explanation-based calibrator keeps improving notably, whereas the performance of probability-based calibrators nearly saturates at a data size of 96. The performance of Few-Shot(NN) with 128 training instances only slightly improves the performance by 3.3%, compared to Few-Shot with 32 training instances. Choosing nearest neighbors as the shots, while being effective when having access to a large amount of data, is not helpful in the extreme data-scarce regime. Calibrating using explanations is an effective way of using a few extra data points that cannot fit in the prompt, which is a pitfall of standard in-context learning.

Finally, RoBERTa finetuned using 128 shots only achieves an accuracy of 54.9%, lagging the performance of GPT-3 based models. The limited training data size is insufficient for finetuning smaller language models like RoBERTa, but is sufficient for P-E+EXPLCALIB to be effective.

4.4 Calibrating ADVHOTPOT

Setup For the ADVHOTPOT dataset, our calibration takes the form of tuning the confidence scores of the predicted answers to better align them with the correctness of predictions. These confidence scores can be used in a “selective QA” setting (Kamath et al., 2020), where the model can abstain on a certain fraction of questions where it assigns low confidence to its answers. We use the area under coverage-accuracy curve (AUC) to evaluate how well a model is calibrated as in past literature (Kamath et al., 2020; Chen et al., 2021; Zhang et al., 2021; Garg and Moschitti, 2021; Ye and Durrett, 2022). The curve plots the average accuracy with varying fractions (coverage) of questions being answered (examples in Figure 5). For any given coverage, a better calibrated model should be able to identify questions that it performs best on, hence resulting a higher AUC.

We experiment with training data set sizes of 6, 32, and 64. We report the results averaged from 5 trials using different training sets. For ADVHOTPOT, we calibrate E-P, which is shown to be more effective than P-E in this setting (Section 2.4). Our approach is also effective for calibrating P-E; please refer to Appendix E for details.

Results We show the AUC scores in Table 4. By leveraging explanations, E-P+EXPLCALIB successfully achieves an AUC of 68.8, surpassing both Few-Shot by 7 points and E-P by 4 points. We note this is substantial improvement, given that the upperbound of AUC is constrained by the accuracy of the answers and cannot reach 100. Figure 5 shows the coverage-accuracy curves of various methods averaged across the 5 training runs. E-P+EXPLCALIB always achieves a higher accuracy
Figure 5: Coverage-Acc curves of various methods on AdvHotpot. E-P+EXPLCALIB are better calibrated compared to uncalibrated E-P as well as the other approaches.

than its uncalibrated counterpart, E-P, under a certain coverage, and the gap is especially large in the most confident intervals (coverage < 50%). E-P+ZHANG ET AL. (2021) is able to calibrate the predictions on this dataset, but still lags our explanation-based calibrator, E-P+EXPLCALIB.

In addition, the explanation-based calibrator can be effective with as few as 32 examples. This is because there are only two parameters (the probability of predicted answer and the explanation-based factor) in the calibrator, which can be easily learned in this few-shot setting. Comparing E-P+EXPLCALIB against FEW-SHOT(NN), using nearest neighbors in the prompt is also able to improve the performance compared to using a fixed set of shots (FEW-SHOT), yet our lightweight calibrator can better utilize such a small amount of data, and learn to distinguish more accurate predictions based on the explanations.

5 Related Work

Our investigation is centered around in-context learning (Brown et al., 2020), which has garnered increasing interest since the breakthrough of various large pretrained language models. Recent work has been devoted to studying different aspects of in-context learning, including its wayward behaviors (Min et al., 2022; Webson and Pavlick, 2022) and approaches to overcome them (Zhao et al., 2021), whereas our exploration focuses on using explanations.

The utility of explanations for few-shot in-context learning has also been discussed concurrently (Nye et al., 2021; Wei et al., 2022; Marasovic et al., 2022; Chowdhery et al., 2022; Lampinen et al., 2022), especially in symbolic reasoning tasks. We differ in that we study the role of more free-form explanations in tasks (QA and NLI, specifically) focusing on textual reasoning over provided contexts. Furthermore, our work particularly focuses on the nature of the explanations generated by GPT-3, which are found to be unreliable. Regarding our use of calibration, similar ideas of explanation-based performance estimation have been applied to other tasks (Rajani and Mooney, 2018; Ye et al., 2021; Ye and Durrett, 2022), but we rely on the free-text explanations generated by the model instead of interpretations obtained through post-hoc interpretation techniques.

More broadly, how to utilize explanations in various forms (textual explanation, highlights, etc.) to train better models is a longstanding problem (Zaidan et al., 2007). Various techniques have been proposed for this purpose. Past work has built a series of pipeline models that first generate the explanations and then make predictions purely based on the generated explanations (Wiegrefe et al., 2021; Zhou and Tan, 2021; Chen et al., 2022). Prior research has also explored using explanations as additional supervision to train joint models that jointly predict the labels and explanations (Hancock et al., 2018; Dua et al., 2020; Lamm et al., 2021; Stacey et al., 2022). Another line of work seeks to aligning the reasoning process of a trained models with the explanations, which is typically done by interpreting a prediction post-hoc through explanation techniques and optimize the distance between the obtained explanation and ground truth explanation (Liu and Avci, 2019; Rieger et al., 2020; Plumb et al., 2020; Erion et al., 2021; Yao et al., 2021). These aforementioned methods all use explanations to update the model parameters and typically require a considerable amount of
explanation annotations to be effective. By contrast, we focus on a setting that treats language models as completely black boxes and only requires few-shot explanations.

6 Caveats and Risks of Explanations from Large Language Models

Our analysis suggests that GPT-3’s internal “reasoning” does not always align with explanations that it generates, as shown by our consistency results. More concerning, the explanations might not be factually grounded in the provided prompt. This shortcoming should caution against any deployment of this technology in practice: because the explanations are grammatical English and look very convincing, they may deceive users into believing the system’s responses even when those responses are incorrect. Section 6 of [Bender et al., 2021] discusses these risks in additional detail. The fact that language models can hallucinate explanations is also found in other work (Zhou and Tan, 2021). This result is unsurprising in some sense: without sufficient supervision or grounding, language models do not learn meaning as distinct from form (Bender and Koller, 2020), so the explanations are not strongly grounded in the same way that a human reader would ground them.

We have shown that even if plugging in explanations does not always lead to improvements, it can still be useful since we can use model-generated explanations to calibrate model predictions. However, there is still progress needed before we can automatically reproduce the human-in-the-loop calibration, as lexical overlap is a weak signal of correctness (see the example in Figure 1). Strong enough entailment models should theoretically be able to perform this task and work across a range of tasks without fine-tuning. This explanation assessing model can even be a language model itself trained for this particular propose to approach the verification tasks for a given domain by in-context learning.

7 Conclusion

We have explored the capabilities of GPT-3 in using explanation in in-context learning for textual reasoning. Through our experiments on two QA datasets and an NLI dataset, we find that simply including explanations in the prompt does not always improve the performance of in-context learning. Our manual analysis demonstrates that GPT-3 tends to generate nonfactual explanations when making wrong predictions, which can be a useful leverage to assess the correctness of the predictions. Lastly, we showcase how to use explanations to build lightweight calibrators, which successfully improve in-context learning performance across all three datasets.

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A Details of Prompts

We show examples of the prompts used for SYNTHETIC, ADVHOTPOT, and E-SNLI in Figure 6, Figure 7, and Figure 8, respectively. Our prompts follow the original formats in Brown et al. (2020). For approaches that use explanations (E-P and P-E), we insert explanations before/after with necessary conjunction words.

**SYNTHETIC: Few-Shot**

Christopher agrees with Kevin. Tiffany agrees with Matthew. Mary hangs out with Danielle. James hangs out with Thomas. Kevin is a student. Matthew is a plumber. Danielle is a student. Thomas is a plumber.
Q: Who hangs out with a student?
A: Mary

**SYNTHETIC: E-P**

Christopher agrees with Kevin. Tiffany agrees with Matthew. Mary hangs out with Danielle. James hangs out with Thomas. Kevin is a student. Matthew is a plumber. Danielle is a student. Thomas is a plumber.
Q: Who hangs out with a student?
A: Because Mary hangs out with Danielle and Danielle is a student, the answer is Mary.

**SYNTHETIC: P-E**

Christopher agrees with Kevin. Tiffany agrees with Matthew. Mary hangs out with Danielle. James hangs out with Thomas. Kevin is a student. Matthew is a plumber. Danielle is a student. Thomas is a plumber.
Q: Who hangs out with a student?
A: Mary, because Mary hangs out with Danielle and Danielle is a student.

Figure 6: Examples of prompts for SYNTHETIC.

**ADVHOTPOT: Few-Shot**

Sir Luigi Arthur Pirandello (12 August 1895 – 4 October 1952) was an John journalist.
Sir Keith Arthur Murdoch (12 August 1885 – 4 October 1952) was an Australian journalist.
Australian Associated Press (AAP) is an Australian news agency. The organisation was established in 1935 by Keith Murdoch.
Sir Nikolai Arthur Trubetzkoy (12 August 1896 – 4 October 1952) was an Covington journalist.
Q: Australian Associated Press was established by a journalist born in which year?
A: 1885

**ADVHOTPOT: E-P**

Sir Luigi Arthur Pirandello (12 August 1895 – 4 October 1952) was an John journalist.
Sir Keith Arthur Murdoch (12 August 1885 – 4 October 1952) was an Australian journalist.
Australian Associated Press (AAP) is an Australian news agency. The organisation was established in 1935 by Keith Murdoch.
Sir Nikolai Arthur Trubetzkoy (12 August 1896 – 4 October 1952) was an Covington journalist.
Q: Australian Associated Press was established by a journalist born in which year?
A: First, Australian Associated Press was established by Keith Murdoch in 1935. Second, Keith Murdoch was born in 1885. The answer is 1885.

**ADVHOTPOT: P-E**

Sir Luigi Arthur Pirandello (12 August 1895 – 4 October 1952) was an John journalist.
Sir Keith Arthur Murdoch (12 August 1885 – 4 October 1952) was an Australian journalist.
Australian Associated Press (AAP) is an Australian news agency. The organisation was established in 1935 by Keith Murdoch.
Sir Nikolai Arthur Trubetzkoy (12 August 1896 – 4 October 1952) was an Covington journalist.
Q: Australian Associated Press was established by a journalist born in which year?
A: 1885. The reasons are as follows. First, Australian Associated Press was established by Keith Murdoch in 1935. Second, Keith Murdoch was born in 1885. The answer is 1885.

Figure 7: Examples of prompts for ADVHOTPOT.
B Details of the SYNTHETIC Dataset

We create a controlled synthetic multi-hop QA dataset. Each context consists of four reasoning chains, where each chain contains two sentences following a template: “A [verb] B. B is [profession].”. We fill in A and B in the reasoning chain templates using randomly selected names from a pool of 50 names. To fill in the [verb] and [profession] in the four reasoning chain templates, we first select two verbs from a pool of 30 verbs and two professions from a pool of 30 professions. Next, we fill in the four chains using the combination of these two verbs and professions, which give a set of completely symmetric chains. Finally, we sample one reasoning chain from all of the four to derive a asking: “Who [verb] [profession]?” (example in Figure 8).

Such a design ensures there are no reasoning shortcuts (Chen and Durrett, 2019), making it a difficult dataset even despite the regular structure of the task. A ROBERTA model needs roughly 500 data points to tackle this problem and achieve near 100% accuracy on the test set.

C Details of Preprocessing ADVHOTPOT Dataset

We preprocess the original Adversarial HotpotQA dataset (Yang et al., 2018; Jiang and Bansal, 2019) in a few ways. We reduce the context length to make it better fit the purpose of testing in-context learning. We use two ground truth supporting paragraphs joined with two adversarial paragraphs to construct the context for each question, instead of using all eight distractors. In addition, we simplify each paragraph by only keeping relevant sentences needed for answering the question (or distracting the prediction); otherwise, the prompt length limit only allows 2-3 examples fit in the input prompt.

We make a challenging test test set of 250 examples by balancing the mix of examples on which prompted GPT-3 makes correct and incorrect predictions. This is done by first running few-shot inference over 1000 examples, and then randomly sampling 125 examples with correct and incorrect predictions, respectively.

Since assessing the accuracy of an answer in QA is hard, and F1 scores do not correlate with the true quality of the answers (e.g., “United States” is a correct answer but has 0 F1 score with respect to the provided ground truth answer “US”) (Bulian et al., 2022), we manually assess the correctness of the answers.

D Reliability Evaluation of E-P on SYNTHETIC and P-E on ADVHOTPOT

In addition to the experiments in Section 3, we evaluate the reliability of E-P on SYNTHETIC and P-E on ADVHOTPOT and present the results in Table 5. The observations here follow those in Table 2. The model-generated explanations are more likely to be consistent than to be factual, no matter how the training explanations are being plugged in the prompt.
Table 5: Left: factuality and consistency of the generated explanations across different datasets. Right: the % of the examples whose explanation factuality is congruent with the prediction accuracy.

|                 | Accuracy | Factuality | Consistency | Accuracy = Factuality |
|-----------------|----------|------------|-------------|-----------------------|
| SYNTHETIC (E-P) | 50.8     | 52.4       | 100.        | 98.8                  |
| SYNTHETIC (P-E) | 51.2     | 52.8       | 100.        | 98.4                  |
| ADVHOTPOT (E-P) | 62.0     | 79.6       | 91.2        | 80.0                  |
| ADVHOTPOT (P-E) | 54.2     | 69.1       | 81.9        | 77.9                  |

E  Calibrating P-E on ADVHOTPOT

Table 6: AUC scores of various methods on ADVHOTPOT under different data conditions. Explanations are also effective for calibrating P-E.

|                  | w/o Explanation | 6L   | 32L  | 64L  |
|------------------|-----------------|------|------|------|
| FEW-SHOT         | 59.6±2.4        | –    | –    | –    |
| FEW-SHOT(NN)     | –               | –    | 61.3±0.9 |      |

|                  | w/ Explanation  | 6L+6E| 32L+6E| 64L+6E|
|------------------|-----------------|------|-------|-------|
| P-E              | 58.4±2.6        | –    | –     | –     |
| P-E+EXPLCALIB    | –               | 62.2±2.8 | 62.6±3.1 |       |

We also experiment with calibrating predictions obtained using P-E on ADVHOTPOT, following the same setup as described in Section 4.4.

As in Table 6, using explanations is also effective for calibrating the predictions obtained using P-E. P-E+EXPLCALIB successfully improves the AUC of P-E from 58.4 to 62.6, outperforming FEW-SHOT and FEW-SHOT (NN).

F  Additional Output Examples

|                  |
|------------------|
| **SYNTHETIC: E-P** |

**Nonfactual**

Jason helps Christopher. Kevin helps Stephanie. James punches Jonathan. Daniel is a typist. Jonathan is a typist. Christopher is a typist. James punches Jonathan. Richard punches Daniel. Stephanie is a tailor.

Q: Who punches a typist?
A: Because James punches Jonathan and Jonathan is a typist, the answer is James.

Matthew blames Tiffany. Lisa is a chef. Christopher helps Kelly. Angela helps Jessica. Rachel blames Lisa. Jessica is a farmer. Kelly is a chef. Tiffany is a farmer.

Q: Who helps a farmer?
A: Because Christopher helps Kelly and Kelly is a farmer, the answer is Christopher.

**SYNTHETIC: P-E**

**Nonfactual**

Richard is a governor. Megan supervises Adam. Tiffany calls Nicholas. Nicholas is a musician. Elizabeth is a musician. Matthew calls Richard. Robert supervises Elizabeth. Adam is a governor.

Q: Who calls a governor?
A: Tiffany, because Tiffany calls Nicholas and Nicholas is a governor.

Anthony believes Justin. John is an engineer. Eric answers Kevin. Amy is an engineer. Justin is a pilot. Sarah answers Amy. Kevin is a pilot. Brandon believes John. Kevin believes Amy.

Q: Who answers a pilot?
A: Sarah, because Sarah answers Amy and Amy is a pilot.

Figure 9: Examples of failure cases on SYNTHETIC. GPT-3 almost always generates nonfactual explanations when giving an incorrect answer, using either P-E or E-P.
**Nonfactual**

"Crestfallen" is a track on "Adore". The single’s artwork is by Yelena Yemchuk. Johnny McDaid is a Croatian professional photographer, painter and film director. Arnjot Berg is a French professional photographer, painter and film director. Yelena Yemchuk is a Ukrainian professional photographer, painter and film director.

Q: Crestfallen’s artwork is done by a photographer of which nationality?
A: Croatian. The reasons are as follows. First, Crestfallen’s artwork is done by Yelena Yemchuk. Second, Yelena Yemchuk is Croatian photographer.

**Inconsistent**

The Pequannoc Spillway is a professional basketball team based in Ellesmere city, United Kingdom. The Silver Lake is a professional basketball team based in Ellesmere harbour, United Kingdom. The Cheshire Phoenix is a professional basketball team based in Ellesmere Port, United Kingdom. Mike DiNunno (born January 29, 1990) is an American-Italian professional basketball player for the Cheshire Phoenix, playing the point guard position.

Q: Where is the basketball team that Mike DiNunno plays for based?
A: Cheshire Phoenix. The reason is as follows. First, Mike DiNunno plays for the Cheshire Phoenix. Second, the Cheshire Phoenix is based in Ellesmere Port.

**Figure 10:** Examples of unreliable explanations generated for ADVHOTPOT using P-E.

**E-SNLI: E-P**

| GT | Premise                          | Question                                              | Answer               |
|----|----------------------------------|-------------------------------------------------------|----------------------|
| True | A female is looking through a microscope. | A lady is observing something True, False, or Neither? | True, because if you’re looking through a microscope you are observing something. |
| False | A person wearing sunglasses, a visor, and a British flag is carrying 6 Heineken bottles. | The person has beer bottles abd has a england flag and glasses. True, False, or Neither? | False, because the person could be carrying any number of items and not just six Heineken bottles. |
| False | A woman and a man are sword fighting. | Two people have engaged in a sword fight and both are dead. True, False, or Neither? | False, because it is impossible for two people to sword fight and both be dead. |
| True | Two construction workers in a truck having a conversation. | Two people are outside a truck. True, False, or Neither? | True, because two people are outside a truck. |
| False | A dog running on grass | A dog is playing outside. True, False, or Neither? | True, because a dog playing outside implies that the dog is playing outside. |
| Neither | A silhouette at the bottom of an escalator. | The silhouette is creeping out the children. True, False, or Neither? | False, because the silhouette is not necessarily creeping out the children. |

**Figure 11:** The completions generated for E-SNLI examples with different ground truth labels (GT) using E-P. GPT-3 sometimes ignores the information from premises when explaining its predictions (examples in the bottom section).