Abstract

Large language models are increasingly capable of generating fluent-appearing text with relatively little task-specific supervision. But can these models accurately explain classification decisions? We consider the task of generating free-text explanations using a small number of human-written examples (i.e., in a few-shot manner). We find that (1) authoring higher-quality examples for prompting results in higher quality generations; and (2) surprisingly, in a head-to-head comparison, crowdworkers often prefer explanations generated by GPT-3 to crowdsourced human-written explanations contained within existing datasets. Crowdworker ratings also show, however, that while models produce factual, grammatical, and sufficient explanations, they have room to improve, e.g., along axes such as providing novel information and supporting the label. We create a pipeline that combines GPT-3 with a supervised filter that incorporates humans-in-the-loop via binary acceptability judgments. Despite significant subjectivity intrinsic to judging acceptability, our approach is able to consistently filter GPT-3 generated explanations deemed acceptable by humans.

1 Introduction

As tasks for natural language understanding have become increasingly more complex, the field of explainable natural language processing (exNLP) has embraced explanations written in free-form natural language. These free-text explanations provide a natural interface between machine computation and human end-users, in contrast to explanations limited to highlighting inputs or predicting numerical forms (Hendricks et al., 2016; Camburu et al., 2018). The dominant paradigm for producing free-text explanations is via direct supervision, i.e., training an autoregressive, generative language model supervised with human-authored explanations (Kim et al., 2018; Park et al., 2018; Camburu et al., 2018; Ehsan et al., 2018; Narang et al., 2020; Wiegreffe et al., 2021, inter alia). However, the need to collect large-scale datasets of human-written explanations is a bottleneck to training these models. Domain expert- or author-annotated datasets are expensive to collect at scale, leading to > 70% of existing free-text explanation datasets being crowdsourced (Wiegreffe and Marasović, 2021). Crowdsourcing high quality written explanations is difficult: even the most meticulous efforts can fail to elicit logically consistent and grammatical explanations, which also

| SNLI (Bowman et al., 2015) |
|----------------------------|
| **Premise:** Dark-haired man wearing a watch and oven mitt about to cook some meat in the kitchen. |
| **Hypothesis:** A man is cooking something to eat. |
| **Label:** entailment |

| GPT-3: Cooking is usually done to prepare food to eat. |
| e-SNLI (Camburu et al., 2018): Meat is cooked in a kitchen, and is a food that you eat. Using an oven mitt implies you’re about to cook with hot utensils. |

| CommonsenseQA (Talmor et al., 2019) |
|-------------------------------------|
| **Question:** What is the result of applying for job? |
| **Answer choices:** anxiety and fear, increased workload, praise, less sleep, or being employed |

| GPT-3: Applying for a job can result in being employed, which is a positive outcome. |
| CoS-E (Rajani et al., 2019): being employed applying for job |

| ECQA (Aggarwal et al., 2021): Applying for a job is followed by attending interview which results in being employed. Applying for a job may not result in the other options. |

Table 1: Greedy free-text explanations generated by GPT-3 that crowd annotators found preferable to human-annotated explanations in the respective datasets. In the first instance, 2/3 annotators preferred the GPT-3 explanation to that from the e-SNLI dataset. In the second instance, 3/3 preferred the GPT-3 explanation to that from CoS-E, and 2/3 preferred it to that from ECQA.
leads to poor-quality models (Narang et al., 2020). Additionally, as there is little standardization in providing instructions and specifications for effective crowdsourcing design, the datasets can be highly varied, making it difficult to compare or combine existing datasets and evaluations (Tan, 2021).

In this work, we ask: without significant direct supervision, can large language models generate reliable explanations? Recent work in NLP has introduced the in-context learning paradigm—providing just a few example training instances via a prompt as input to a large language model. Without performing any fine-tuning, in-context learning has achieved competitive performance on certain classification and generation tasks (Radford et al., 2019; Brown et al., 2020; Shin et al., 2020; Schick and Schütze, 2021a, i.a.). Surprisingly, we find that, in a human subjects study of head-to-head comparisons, explanations generated via in-context learning with GPT-3 (Brown et al., 2020) are frequently competitive with the human-written explanations in the datasets themselves.

While this result calls into question the efficacy of the direct supervision paradigm, we demonstrate via two additional human subjects studies that GPT-3 generated explanations still have significant room for improvement along axes such as providing new information (i.e. avoiding repetition), and supporting the label. In particular, when we ask whether users find explanations to be acceptable, less than half the GPT-3 generated explanations are found to be so with high annotator agreement.

However, when we sample further candidate explanations from the model, we find this ratio substantially increases. This leads us to ask—can we leverage acceptability judgments as supervision to improve over the default GPT-3 generations? We investigate an overgenerate-and-filter human-machine collaboration to improve GPT-3’s free-text explanation generation (see illustration in Figure 1). Specifically, we collect simple binary “acceptability” judgments as a source of supervision for multiple explanation candidates sampled from the model, inspired by prior work (Ziegler et al., 2019; Stiennon et al., 2020; West et al., 2021). Despite intrinsic subjectivity in acceptability ratings (Tan, 2021), we show that a supervised filtration model can consistently select human-identified, high-quality explanations better than strong baselines that do not incorporate this human intervention.

In summary, our main findings are:

1. In-context learning with GPT-3 produces surprisingly competitive explanations off the shelf, providing a promising alternative to free-text explanation corpora collection;
2. a supervised filtration approach is an effective means of incorporating human supervision to select high-quality generated explanations; and
3. even after filtration, GPT-3 explanations still have plenty of room to improve, indicating the challenging nature of the acceptability prediction task.

We will release our code and human-annotated data.

## 2 Few-Shot Prompting is Competitive with Crowd-Sourced Datasets

Is in-context learning with GPT-3 a viable strategy to generate free-text explanations? To this end, we investigate three research questions:

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1. [https://github.com/allenai/few_shot_explanations/](https://github.com/allenai/few_shot_explanations/)
• Can improving prompt quality in a few-shot setting improve GPT-3 generated explanations? (§2.1)
• Are few-shot, GPT-3 generated explanations preferable to crowdsourced, gold-standard ones? (§2.2)
• Along what fine-grained dimensions are GPT-3 explanations preferred? (§2.3)

In-context learning for explanations. We use GPT-3 Davinci (Brown et al., 2020), an autoregressive language model with ~175B parameters trained on a large dataset of text scraped from the internet. We prompt the model with several (question, answer and explanation) triplets, followed by an unexplained question-answer instance for which we expect the model to generate an explanation, without updating any parameters (see Table 2). We use a total of 115 randomly sampled train instances to create our prompts; each prompt consists of 8-24 randomly selected examples from this set. For each instance, we generate a single explanation with greedy decoding. More details about prompt construction are in Appendix A.

Explanation tasks and datasets. We consider two English tasks: CommonsenseQA and SNLI (see Table 1). CommonsenseQA (Talmor et al., 2019) is a multiple choice task posed over commonsense questions. Crowdsourced free-text explanations for instances in CommonsenseQA are provided in the CoS-E v1.11 (Rajani et al., 2019) and ECQA (Aggarwal et al., 2021) datasets. ECQA was released to address the quality issues of CoS-E (Narang et al., 2020); we consider both to provide perspective on the impact of prompt quality. ECQA explanations are counterfactual, i.e., annotators were instructed to not only explain the correct answer choice but also why the other answer choices are incorrect. Our second task is SNLI (Bowman et al., 2015), which involves inferring whether a given hypothesis sentence entails, contradicts, or is neutral towards a premise sentence. Crowdsourced free-text explanations are provided in the e-SNLI dataset (Camburu et al., 2018). In this work, we assume access to the gold label, and focus only on producing an explanation for each instance. For each task, we report results on a fixed, randomly-sampled 250-instance test set not observed during prompt tuning or model development.

Head-to-head evaluations. Our human studies in §2.1 and §2.2 are head-to-head comparisons of two explanations generated under different conditions for the same dataset instance. We evaluate the quality of explanations via a large-scale human subjects study using Amazon Mechanical Turk (AMT). Participants in our evaluation study are instructed to make a preferential selection between two explanations, given the instance and gold label, on a 5-point Likert scale. We report annotator agreement using Krippendorff’s $\alpha$ (Table 14; Krippendorff, 2011). Appendix B contains further details of interface design, qualification, quality control, and annotator agreement.

Existing, automatic, reference-based metrics for evaluation of generated explanations cannot capture different dimensions of human judgments (Cliciu et al., 2021; Kayser et al., 2021).

Table 2: Example of a prompt containing 3 training examples from SNLI: presented are the premise/hypothesis pairs, the gold labels, and the explanations (written by us) that act as input to GPT-3 (in practice, we use 8-24 examples per prompt). The text generated by the model acts as the free-text explanation. In this case, the model greedily auto-completes (given 12 examples): “A dog cannot carry something while asleep”. Additional details on prompt construction are in Appendix A.

2 Existing, automatic, reference-based metrics for evaluation of generated explanations cannot capture different dimensions of human judgments (Cliciu et al., 2021; Kayser et al., 2021).

3 The choices are: explanation 1 preferred, explanation 1 weakly preferred, both equal, explanation 2 weakly preferred, or explanation 2 preferred.
2.1 RQ1: Can improving prompt quality improve GPT-3-generated explanations?

Table 3: Human-participant evaluation results in the head-to-head setting for 250 GPT-3 explanations generated conditioned on either our handwritten explanations or explanations from the existing dataset. The percentage of participants who preferred our-prompted GPT-3 explanations, gold-prompted GPT-3 explanations, or thought the explanations were equal is presented. Each explanation has 3 annotations.

| Dataset  | Preferred GPT-3 Expl. (%) by Prompt Source |  |
|----------|-------------------------------------------|--|
|          | Gold Prompts | Tie | Our Prompts |  |
| CoS-E    | 6.93 | 13.47 | 79.6 |  |
| ECQA     | 15.87 | 9.47 | 74.67 |  |
| e-SNLI   | 30.8 | 26.8 | 42.4 |  |

Given known quality issues in some of our corpora, our first question is: can we improve GPT-3 generations simply by conditioning on higher-quality instances in the prompts? For prompt construction, we replace the 115 gold-standard (crowd-sourced) explanations from the original datasets with explanations written carefully by the authors of this paper (see Table 12 for examples). Our prompts are used in context with GPT-3 to generate a different set of explanations on the same test data. We perform a head-to-head comparison of the GPT-3 generations conditioned on the prompts with explanations we authored vs. the GPT-3 generations conditioned on the explanations from the original corpora.

Results of the head-to-head study are presented in Table 3. For these experiments, average Krippendorff’s $\alpha$ is 0.31. We find that, for all corpora, generations conditioned on our explanations outperform generations conditioned on dataset-derived explanations. This effect is especially pronounced for CommonsenseQA; GPT-3 even reproduces known data artifacts in the CoS-E corpus when prompted with the dataset (such as the phrase “rivers flow trough valleys”, which appears 10 times in the prompt set). GPT-3 also appears to emulate the counterfactual nature of ECQA explanations, which may, in-part, explain annotator preferences in that case. These results provide evidence that a few-shot setting may allow an end-user control over explanation format and quality by authoring as few as 8-24 examples. For subsequent experiments, we use the prompts we authored when prompting GPT-3.

2.2 RQ2: Are GPT-3 generated explanations preferable over gold-standard ones?

Our next head-to-head comparison compares explanations generated by GPT-3 to the (crowdsourced) gold-standard explanations in the original datasets; the results of this evaluation are shown in Table 4 for both tasks. For these experiments, average inter-annotator agreement was $\alpha = 0.37$.

For CommonsenseQA (with explanations from CoS-E and ECQA), the GPT-3 greedily-decoded generations are often preferred over gold-standard explanations in both datasets. For CommonsenseQA, these results are not too surprising: CoS-E explanations are often not grammatical, and ECQA explanations, being counterfactual, likely provide too much information (we don’t show the incorrect answer choices). What is surprising, however, is that GPT-3 generations are competitive with the e-SNLI corpus, even though that corpus is generally regarded as high quality. While GPT-3 doesn’t always win, the gold-standard free-text explanations from the corpus serve as a reasonable upper bound for what a supervised explanation generation model trained on them could be expected to produce. Some examples of GPT-3-preferred explanations, along with human preference annotations, are given in Table 1.

2.3 RQ3: What types of explanations does GPT3 output?

While the head-to-head results of §2.1-2.2 are promising, pairwise evaluations can only offer perspective on the relative quality of paired generations. Are crowd annotators simply comparing explanations on surface-level features like fluency or grammaticality? We seek to understand the fine-grained aspects leading to GPT-3’s success, and the aspects along which improvements are possible.

We design a second human study to collect ab-
Figure 2: Absolute evaluation results for explanations generated by GPT-3 vs. gold-standard explanations on the 250-instance test sets for two tasks. For CommonsenseQA, GPT-3 generations are compared to the CoS-E (top) and ECQA (middle) datasets. For SNLI, GPT-3 generations are compared to the e-SNLI dataset (bottom). Interpretations of the numerical scores on the y-axis are detailed in Table 5. *Amount Info is the only attribute for which a value of 0 is preferred to a value of 1. Each datapoint is the mean score of 3 annotators. Means and standard errors of each distribution are in Table 16.

solute Likert-scale ratings for each explanation across six axes split into two groups. The first three axes capture surface-level features: generality, grammaticality, and factuality. The last three are designed to capture aspects of explanation quality related to the instance it explains: whether new information is introduced (a requirement for non-vacuous explanations), whether it supports the gold label, and whether the amount of information given to justify the label is sufficient (see Table 5). We explain our design process and the prior work in psychology that informs each axis in Appendix B.2. We collect absolute judgments for both gold-standard and GPT-3-generated explanations across all six fine-grained explanation qualities; these results are presented in Figure 2.

Unsurprisingly, for both tasks, GPT-3 explanations do well in all 3 of the surface-level categories. For the CommonsenseQA task, GPT-3 explanations are judged by human evaluators to be more general, factual, grammatical, and containing the right amount of information compared to both the CoS-E and ECQA corpora; GPT-3 explanations exhibit relatively low variance in these categories. GPT-3 explanations are judged to be supportive of the label at a level only slightly worse than ECQA, and substantially better than CoS-E. For SNLI, we
observe that GPT-3 generated explanations have nearly identical ratings to e-SNLI explanations (despite being evaluated independently).

GPT-3 explanations have substantial room to improve in providing new information (mean=0.1 for both tasks) and supporting the label (mean=0.5 for CommonsenseQA and −0.1 for SNLI). These axes are crucial to ensuring explanations are not vacuous and are on-topic.

We also note that, despite following rigorous crowdsourcing practices (Appendix B.4), inter-annotator agreement is relatively low and highly variable across the five absolute studies (Table 15). In an ideal setting, machine-generated explanation quality should be unambiguous enough to elicit high scores across a group of annotators.

3 Is GPT-3 all we need?

In §2, simply asking users for coarse, pairwise explanation preferences (§2.1-2.2) resulted in higher and more consistent inter-annotator agreement scores than asking about fine-grained attributes. This motivates us to perform an absolute human-subjects study distilling the experiments of §2.3 into one question: are GPT-3 explanations acceptable? Despite the apparent subjectivity of this question, in contrast to other axes of evaluation, we find higher inter-annotator agreement (Krippendorff’s α) of 0.34-0.41 for CommonsenseQA and 0.47-0.51 for SNLI. Annotator agreement rates may also point to just how acceptable a given explanation is, e.g., an explanation rated as acceptable by 2/3 annotators may be more controversial than one rated acceptable by 3/3.

Following prior work in crowdsourcing binary acceptability judgements (Ziegler et al., 2019; Stiennon et al., 2020; West et al., 2021), we gather three binary acceptability judgments from crowd annotators for greedy GPT-3 explanations conditioned on our authored explanations. Our crowdsourcing interface is provided in Appendix B.3. There are four possible labels to assign an explanation: 0/3, 1/3, 2/3, or 3/3 annotators labeled it acceptable. When considering only explanations rated positively by 3/3 annotators as “acceptable”, for CommonsenseQA, only 46.3% of generated explanations are acceptable; for e-SNLI, only 31.5%. Because GPT-3’s greedy decoding algorithm does not account for acceptability, we hypothesize that equally or more informative explanations can be generated via other decoding mechanisms. Inspired by Holtzman et al. (2021)’s experiments that demonstrate the highest probability zero-shot generations from LMs are frequently incorrect in QA settings, we stochastically sample (from the full probability mass) 4 additional generations from GPT-3 using the same prompts. We collect the same 3 acceptability annotations per sample. For each instance, we now have 5 candidate explanations (1 greedy, 4 sampled) annotated for acceptability by 3 annotators.

While these stochastic samples exhibit lower acceptability than the greedy-decoded explanations (25.1% for CommonsenseQA; and only 11.3% for e-SNLI), their addition surprisingly results in a much higher proportion of instances that have at least one acceptable explanation. For CommonsenseQA, while the greedy explanation was judged to be acceptable in only 46.3% of cases, 79.5% of instances have an acceptable candidate at the 3/3 agreement level among the 5. Similarly, for e-SNLI, this number goes from 31.5% to 51.2%.

In conclusion, we find:
1. for our corpora, high likelihood greedy samples from GPT-3 are acceptable less than half the time;
2. better explanations are possible, i.e., there is significant headroom over greedy decoding in generating highly acceptable explanations, and;
3. a simple way of generating better explanations is to sample multiple candidates from GPT-3.

The challenge in this setting is that GPT-3 alone cannot discern which of its samples are acceptable. While future work would be well-suited to explore whether or not unsupervised decoding approaches can improve acceptability (e.g., by using logical constraints), we explore training a supervised filter directly on the collected labels.

4 Improving Explanation Generation with an Acceptability Filter

We train a supervised classification model to predict the previously-described binary acceptability ratings for explanations from crowd annotators (see §3). Our key intuition is that by re-framing the role caused by intrinsic subjectivity, and that they can be improved upon.
We collect 5 GPT-3 generations each for 1,250 in-
Table 6 contains corpus statistics. From the original
Table 6: Statistics of the binary acceptability ratings
not contribute to the training data.

App. 2019), we collect an additional set of annotations
2019, and the generated explanation, the task involves
predicting whether the explanation is acceptable
given the instance.

While we still evaluate at test-time with the
schema that {3/3} agreement scores are deemed
acceptable and all others ((0/3, 1/3, 2/3)) are
deemed unacceptable. We find that treating
{2/3, 3/3} agreement instances as acceptable and
{0/3, 1/3} instances as unacceptable during train-
ing performs best. The result is a relatively bal-
anced binary classification task over explanations (Table 6).
We also experiment with a setting of less
training supervision, where we assume access to
only one of the three annotator labels (randomly
selected) rather than aggregating them. After se-

Acceptability judgement corpus details. We
collect binary acceptability judgments over GPT-3
generations for both Commonsense QA and e-SNLI:
Table 6 contains corpus statistics. From the original
CommonsenseQA and SNLI corpora, we sample
991 and 1K instances, respectively. Combining
these with the same held-out test set from previous
experiments results in a dataset of 1,250 instances
in a 72/8/20% train/val/test ratio. Then, for each
instance, we sample 5 GPT-3 generations using our
authored prompts. Finally, for each generation, we
collect three binary acceptability judgments from
each of annotators (from explanation-authors to binary
judges), we can alleviate the need for collecting a
large-scale free-text explanations dataset: the re-
sult is a simpler, cheaper, and easier crowdworking
setup to administer. And, in §4.1, we find that the
filter can be trained with a relatively small amount
of binary human judgments. Figure 1 presents an
overview of our pipeline.

| Dataset | Split     | # Instances by Agreement | Total |
|---------|-----------|--------------------------|-------|
|         | 0/3       | 1/3                      | 2/3   | 3/3   |
| Com.QA  | Train     | 932                      | 1078  | 1194  | 1296  | 4500  |
|         | Dev       | 105                      | 91    | 132   | 127   | 455   |
|         | Test      | 298                      | 227   | 328   | 397   | 1250  |
| SNLI    | Train     | 2372                     | 805   | 621   | 702   | 4500  |
|         | Dev       | 272                      | 87    | 65    | 76    | 500   |
|         | Test      | 678                      | 225   | 166   | 181   | 1250  |
|         | Test_Crowd2| 666                     | 234   | 179   | 171   | 1250  |

In order to validate that our system is not over-
fitting to a single group of annotators (Geva et al.,
2019), we collect an additional set of annotations
for the test set of SNLI from a group of annota-
tors who did not participate in any of our previous
annotation tasks (“Test_Crowd2”). If the model
generalizes well, it should also be able to perform
similarly on a test set annotated by people who did
not contribute to the training data.

4.1 Acceptability Filter
We fine-tune two sequence-to-sequence architec-
tures, T5-Large (Raffel et al., 2020) and T0-3B
(Sanh et al., 2021) to perform the acceptability clas-
sification task on individual (instance, explanation,
label) pairs. Concretely, given the problem instance
e.g., premise/hypothesis for SNLI, the gold label,
and the generated explanation, the task involves
predicting whether the explanation is acceptable
given the instance.

Our results don’t significantly change if a 2/3 cutoff is
used at test time instead: Appendix E contains the comparable
results.

4.2 Evaluation
We consider two evaluation settings. The first
is instance-level (also referred to as “select-1”),
where the system returns one explanation (selected
from the set of five) for each instance. We return the

This is a slightly more competitive baseline than greedy;
greedy usually (but not always) produces the highest-
likelihood explanation. According to GPT-3, a sampled expla-
nation has a lower NLL than the greedy explanation for only
2.8% and 3.6% of instances, respectively, of our Common-
senseQA and SNLI test sets.
Table 7: Results for acceptability classifiers trained on CommonsenseQA. Subscripts indicate standard error over models trained with 5 different random seeds. “w/o HA” = without human agreement.

| Model/Split | “Select-1” Acc@3/3 | Expl-level AP@3/3 |
|-------------|--------------------|-------------------|
|             | Dev                | Test              | Dev                | Test              |
| Random      | 20.8±1.2           | 30.6±2.1          | 27.4±1.1           | 31.6±0.4          |
| Constant    | —                  | —                 | 27.9               | 31.8              |
| NLL         | 41.8               | 52.0              | 42.4               | 45.6              |
| T5-L Expl-only | 40.2±1.9          | 49.8±1.1          | 43.5±1.5           | 50.0±1.9          |
| T0-3B Expl-only | 42.6±1.4         | 47.3±1.6          | 41.2±2.0           | 54.1±1.7          |
| T5-L w/o HA | 46.6±2.3           | 54.4±2.2          | 47.0±2.3           | 56.9±3.8          |
| T5-L        | 46.4±2.3           | 55.4±2.1          | 45.3±1.4           | 58.3±1.5          |
| T0-3B w/o HA| 48.4±2.0           | 57.4±2.8          | 44.9±2.3           | 59.8±2.2          |
| T0-3B       | 48.6±0.9           | 59.9±1.1          | 49.7±1.0           | 64.0±1.5          |
| Oracle U.B. | 78.0               | 82.0              | 100.0              | 100.0             |

The effect of multiple training annotations. In some cases, performance improves if the training instances are labeled with the consensus of three annotators (vs. the singularly annotated case “w/o HA”), though the effects are not consistent. In most cases, we do see reduced variance across random seeds by using consensus agreement. However, given that training on consensus requires 3x the annotations, the gains may not outweigh the data collection effort.

Our model doesn’t overfit to specific annotators. Reassuringly, the performance of our model when evaluated on the SNLI test set labeled by separate annotators (“Test_Crowd2”) is comparable to the original test set (instance-level accuracy drops a few points, but explanation-level AP slightly rises). Importantly, we also reach the same conclusions on this test set regarding the superior performance of our model with respect to the baselines.

In summary: We have demonstrated the effectiveness of modeling binary crowd judgements of acceptability as a means to select candidates from GPT-3 which are human-acceptable at a high agreement. In the method that does not leverage human agreement, this is done with only 5k datapoints. The room between our best model and the upper-bound oracle indicates that there is still substantial room for improvement in the select-1 setting. Future work may investigate sampling more explanations at test-time, or incorporating other sources of supervision signal.

8Because the input instances are identical in the select-1 setting between the 5 explanation candidates, any improvement over the explanation-only baseline is evidence of feature interactions, specifically.
with 5 different random seeds. “w/o HA” = without human agreement.

Table 9: Randomly-selected instances that our filter predicted differently than NLL at the “select-1” task, and got correct but NLL got incorrect.

| Question: Where would there be an auditorium with only a single person speaking? | Answer choices: theater, park, university campus, crowd, or lights | NLL-Predicted Explanation: An auditorium is a large room used for lectures, and a single person speaking is likely to be a lecture. | Filter-Predicted Explanation: On university or university-like campuses, the auditoriums are often used for lectures or other University events, where a single person might be speaking. |
|---|---|---|---|

Table 10: Randomly-selected instances that our filter model predicted differently than NLL at the “select-1” task, and got incorrect but NLL got correct.

5 Related Work

Free-text explanation generation. Some of the first works to propose free-text explanation generation from neural language models did so for computer vision applications (Hendricks et al., 2016; Park et al., 2018; Kim et al., 2018) and natural language inference (Camburu et al., 2018). All of these methods relied on supervised datasets to train the explanation generator. Others have proposed to generate explanations or clarifications to improve task performance in a supervised (Rajani et al., 2019) or unsupervised (Shwartz et al., 2020) manner.

Latcinnik and Berant (2020) propose a method to generate free-text explanations supervised only on task signal, and Brahman et al. (2021) use sources of weak supervision to generate explanations for the defeasible inference task. Paranjape et al. (2021) design hand-crafted templates and use a mask-infilling approach to produce contrastive explanations from pretrained language models. Concurrent work (Marasović et al., 2021) also investigates prompting large language models in a few-shot manner for free-text explanation generation. They study the effects of different prompt formats.
and model size on explanation quality. In contrast, we investigate generated explanations through the lens of 3 different crowdsourcing evaluations, study the effects of written prompt quality, and investigate a filtration method trained on human acceptability judgements.

**Prior supervised filtration schemes.** While overgeneration+filtration has yet to be applied to free-text explanations, our pipeline is inspired by prior work where binary preferences or acceptability signals from crowdworkers have been used to fit models to human preferences (Ziegler et al., 2019; Stiennon et al., 2020). West et al. (2021), for example, demonstrate that GPT-3 + a supervised acceptability filter can generate a high-quality causal knowledge graph. However, (1) it’s not immediately clear that a similar setup will work for free text explanations, given the intrinsic subjectivity of “acceptability”; and (2) while West et al. can simply discard unacceptable generations and not include them in the final corpus, our more stringent “select-1” setting necessitates generating at least one acceptable explanation per instance. As a result, our success conditions and evaluation metrics also differ.

6 Conclusions

We have presented results demonstrating the strength of GPT-3 at producing plausible free-text explanations for NLP task instances, as judged by crowd annotators. We have additionally proposed a method for improving model-generated explanations by modeling a human acceptability filter for a set of generations. These results establish an upper-bound on the plausible free-text explanation generation task, which should guide future work that seeks to improve free-text explanations via neural or neuro-symbolic systems that inject other sources of knowledge (Brahman et al., 2021; Majumder et al., 2021; Saha et al., 2021). While human rationales for decision making are not necessarily the same as model rationales, the goal behind modeling human acceptability is to build trust with a human user. This trust may or may not be warranted (Jacovi et al., 2021); future work should investigate cases in which trust is warranted vs. those in which it is not (for example, by looking at explanations for incorrect label predictions). Such experiments could help to reveal cases in which the model could mislead an end user, and begin to provide insight into the faithfulness of GPT-3-generated explanations.

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A Prompt Construction

Following Perez et al. (2021), we avoid prompt tuning on the full training and development sets of the datasets studied, in order to ensure that our methods represent a true few-shot setting. To develop the initial prompt design, we experimented with no more than 10 different layouts in the GPT-3 Sandbox platform using 15 training examples on the CoS-E and e-SNLI datasets. For subsequent prompt design, we again used these 15 training examples for each dataset from which we sampled 6 prompts, along with a fixed 100-example “development set” randomly drawn from the training set. We preserve the “few-shot” approach by using a maximum of these same 115 instances to develop our prompting methods. For these 115 examples, the authors of this paper manually wrote high-quality explanations to be used as prompt examples (Table 12). As presented in Table 2, we found that structuring SNLI as a question-answering task achieved the best performance, similarly to Zhao et al. (2021).

We provide an example of our CommonsenseQA prompt in Table 11.

In-context learning methods have been shown to have high variance based on hyperparameters including example order, number of examples given, and which examples are given (Jiang et al., 2020; Zhao et al., 2021; Lu et al., 2021). While these values have not been standardized, two prominent papers, Schick and Schütze (2021b) and Brown et al. (2020), use 32 and 64 prompt examples, respectively. Due to the 2049-token limit of the OpenAI GPT-3 API and the fact that the addition of explanations elongates each prompt instance, we find the maximum number of examples the API can accommodate is 24 for CoS-E, e-SNLI, and our handwritten explanations and 16 for ECQA.

The focus of this work is not on finding the optimal prompt, but on developing a general strategy for few-shot explanation generation that could be successful when no additional (large) validation set for tuning is available. Therefore, to provide as robust of an expected performance estimate as possible, we do not tune the additional hyperparameters, instead sampling them to approximate
Let’s explain classification decisions.

**question:** When remembering a tragedy in the past, what do many people feel?

**pain, depression, knowing, knowledge, or nostalgia?**

**depression**

**why?** Remembering a past tragedy can resurface feelings that arose in response to that tragedy. Because tragedies are not positive events, it’s possible that sadness and depression could arise from remembering it.

###

**question:** What do people do sometimes when they find a good deal?

**race cars, murder each other, believe in god, fight each other, or fear death?**

**fight each other**

**why?** Malls sometimes have sales, e.g., on black friday, when they offer good deals; however, the items are sometimes in limited supply, which can cause alterations between folks, each trying to buy the same item.

###

**question:** What does someone who has a greed for energy do?

**buy food, lie, get, cause businesses to grow, or win?**

**buy food**

**why?** When consumed, food provides energy and satisfies the greed for it.

###

**question:** Immediately after peeing, a person’s bladder is what?

**full, empty, filled, stretchable, or collapsed?**

**empty**

**why?**

Table 11: Example of a prompt with 3 training examples from CommonsenseQA: presented are the question and answer choices, the gold labels, and the explanations (written by us) that act as input to GPT-3 (in practice, we use 8-24 examples). The text generated by the model acts as the free-text explanation. In this case, the model greedily auto-completes (with 8 examples): “After peeing, the bladder is empty.”

Table 12: Examples of explanations used as prompts from various sources, including our handwritten explanations.

**SNLI (Bowman et al., 2015)**

| Premise | Hypothesis | Label | Our Explanation |
|---------|-------------|-------|------------------|
| A person on a horse jumps over a broken down airplane. | A person is training his horse for a competition. | neutral | While it is possible that jumping a horse over an obstacle is part of a training routine for a competition, it is also possible that the horse ride is being done for pleasure, not necessarily for a competition (sp). |

**e-SNLI Explanation:** the person is not necessarily training his horse

| Premise | Hypothesis | Label |
|---------|-------------|-------|
| Children smiling and waving at camera | There are children present | entailment |

| Our Explanation | |
|-----------------|------------------|
| Since the children are part of the event of smiling at the camera, they are present at the event under discussion. | |
| **e-SNLI Explanation:** The children must be present to see them smiling and waving. |

**CommonsenseQA (Talmor et al., 2019)**

| Question | Answer choices: | Our Explanation |
|----------|-----------------|------------------|
| A cat can’t talk, but a cat can what? | sleep all day, meow, shed fur, see king, live many years | |

| Our Explanation | |
|-----------------|------------------|
| A cat can meow as a way to vocalize. | |
| **CoS-E Explanation:** the cat is a small carnivorous mammal |

| ECQA Explanation | |
|------------------|------------------|
| A cat can meow but cannot see the king. Meowing is how a cat communicates and not by sleeping all day, shedding fur or by living many years. | |

| Question | Answer choices: | Our Explanation |
|----------|-----------------|------------------|
| "There are 10 apples on an apple tree. Three fall off. Now there are X apples." What is this an example of? | park, coloring book, garden center, math problem, gravity | |

| Our Explanation | |
|-----------------|------------------|
| A math problem is usually posed as a question that requires some operation such as subtraction or addition to answer. | |
| **CoS-E Explanation:** webmath is designed to help you solve ECQA Explanation: Math problem is an arithmetical problem of addition, subtraction, multiplication or division. So “There are 10 apples on an apple tree. Three fall off. Now there are X apples.” is a math problem. All the other options aren’t problems to be examples of the given question. | |

Table 12 shows a few non-cherry-picked examples of our handwritten explanations used as prompts relative to the datasets.

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9 Perez et al. (2021) show that performing cross-validation or tuning via maximum description length over a small validation set does not significantly outperform random sampling of these values.
B Crowdsourcing Details

B.1 Head-to-Head Interface Details
We show the user the task input and gold label, and ask them to select which of two explanations best explains the answer. We instruct workers to consider the gold label to be correct even if they disagree with it (CommonsenseQA instances can be subjective) and to ignore minor grammar and spelling mistakes such as improper upper-casing. Figures 3 and 4 show the evaluation interface.

B.2 Absolute Interface Details
Figures 5 and 6 show the absolute evaluation interface. Our interface is inspired by prior work from psychology and the social sciences (Leake, 1991; Gopnik, 1998; Lombrozo, 2007; Zemla et al., 2017; Chiyah Garcia et al., 2018; Clinciu et al., 2021; Sulik et al., 2021). We iterated over 3-4 versions of the questions and UI design until we had optimized agreement rates as much as possible. Our resulting two-part evaluation consists of 5 questions:

Part 1: Context-Independent Evaluation
We first assess the explanation in isolation, i.e., these questions are presented to the user without revealing the question/context that the explanation is attempting to address:

1. How factual is this statement? (generally false, sometimes or partially true, generally true, or need more information to judge). This question is designed to test both generality (can the explanation’s truthfulness be ascertained or is more information needed?) and factuality, which aligns with “compatibility with receiver’s existing beliefs” and that the best explanation is the “most likely” explanation from the receiver/user’s perspective (Lombrozo, 2007; Zemla et al., 2017; Sulik et al., 2021). Generality is coded based on whether a truthfulness answer is selected (considered to be general) or whether the “need more information to judge” choice is selected (considered not to be general).

2. Is this statement grammatical? (yes or no) This question is designed to test for clarity, aligning with characteristics such as coherence (Lei et al., 2016) and human-likeness and understandability (Ehsan et al., 2019).

Part 2: Context-Dependent Evaluation
We next show the user the question (premise and hypothesis for SNLI) and gold answer that the explanation was conditioned on. We then ask:

1. Does the explanation provide new facts, information or reasoning not stated in the question and answer? (yes or no) In our preliminary experiments, we found some explanations simply restate the question declaratively with the answer filled in. This question addresses the distinction between “validity” and “utility” (Leake, 1991): an explanation can be valid (i.e., a restatement of the question with the answer filled-in might be correct), but not useful; utility is defined by whether an explanation “satisfies an explainer’s need for information”. And while utility is best understood in the context of real-world applications (Lai et al., 2020), we nonetheless aim to identify vacuous explanations that do not provide new information.

2. Is the new information relevant to justifying the answer? (yes or no) New information, if provided, “should be compatible with our existing beliefs, and consistent with the evidence and with itself” (Zemla et al., 2017). This question is designed to test whether the information provided supports the label. The specific interpretation of “relevance” is purposefully left to the annotator.

3. How much information does the explanation have to justify the answer? (not enough, enough, or too much) The final question is designed to test the extent to which the provided novel information is adequate or sufficient (Kim et al., 2016; Lei et al., 2016; Ehsan et al., 2019).

We only ask Questions 2 and 3 if the answer to Question 1 is “yes” because they regard the new facts, information, or reasoning. We found that most prior work tends to lump added-value, relevance, and adequacy judgements into one “informative-ness” judgement (Clinciu et al., 2021), which we felt was too course to allow for meaningful error analysis.

B.3 Acceptability Interface Details
Figures 7 and 8 show the binary acceptability interface.

10 This decision is inspired by prior work in psychology, which finds that explanations are only good “to the extent that people find [them] satisfying” (Gopnik, 1998; Sulik et al., 2021).

11 In practice, we do not find Turkers use the “too much information” option often, except in the case of ECQA dataset explanations. We included the option because succinctness is an oft-cited explanatory virtue (Lombrozo, 2007; Zemla et al., 2017; Chiyah Garcia et al., 2018).
B.4 Quality Control and Payment

We use Amazon Mechanical Turk (AMT), and calculate pay on a rate of $15/hour. Every few batches, we check to ensure that the median time taken per annotator amounts to approximately this pay rate. While annotators do tend to speed up the more HITs we released, first-round median times were approximately 30 seconds per head-to-head evaluation HIT (thus paid at $0.12 each), 1 minute per absolute evaluation HIT (thus paid at $0.25 each), and 35-39 seconds per acceptability HIT (5 explanations; paid at $0.20 each).

We require annotators to be located in either Australia, Canada, New Zealand, the United Kingdom, or the United States, as a proxy for English competency.12 We require a past HIT approval rate of > 98% and > 5000 HITs approved. We do not allow annotators to participate who were previously on a block list from our past AMT studies.

Annotators must complete a qualifying exam in order to participate in the main annotation tasks. The qualifying exam consists of 3 HITs in the same format as the main absolute evaluation task for CommonsenseQA We pay $2.25 for the qualifying exam. There are 9-18 questions in total (3-6 questions per HIT), some of which are only answerable conditioned on previous answers. A user who answers “no” to question 3, for example, will not be asked to answer questions 4 and 5. Given the challenging and sometimes ambiguous nature of some of the questions, for the first run of the qualification exam, we manually awarded qualifications by inspecting the annotators’ answers. Scores for the first run compared to our answers (out of 17 annotators attempting) ranged from 5 to 14 out of 18. The median accuracy was 11 out of 18, and we find that awarding the qualification to those with scores at or above the median aligns closely with our manual inspection. We thus use this score to assign qualifications in future iterations.

Because it is necessary that annotators understand the task before they can evaluate explanation quality (Wiegrefe and Marasović, 2021), for tasks that are more difficult, i.e., NLI, we additionally require annotators to pass (score of 7 or above) a task-specific qualification exam with 8 questions, paid at $1.25.

In order to track quality throughout evaluation, we compute inter-annotator agreement using Krippendorff’s $\alpha$ and use a hidden built-in Javascript function to compute time per HIT spent. If any annotator completed the tasks in an unreasonably low time, or removing their annotations substantially improves Krippendorff’s $\alpha$, we remove their annotations and re-annotate their instances. We additionally ensure that each experiment has a substantial number of distinct crowdworkers to mitigate individual annotator bias, reporting this as well as the mean and median number of HITs completed by each in Table 13.

B.5 Statistics

The number of distinct crowd annotators, the median number of HITs completed, and inter-annotator agreement for each experiment can be found in Table 13, Table 14, and Table 15.

C 2/3 Acceptability Statistics

When we treat explanations rated by at least 2/3 annotators as “acceptable”, for CommonsenseQA, 77.9% of greedy-decoded explanations are acceptable; for SNLI, 51.0%. 50.5% of sampled explanations are acceptable; for SNLI, 23.5%. Out of the set of 5 (1 greedy + 4 stochastic), 97.7% of CommonsenseQA instances have at least one acceptable explanation, and 79.5% of SNLI.

D Filter Model Details

We split the 4,955 distinct annotated explanations for CommonsenseQA (5000 for SNLI) into a train/dev set of 4500/455 (4500/500 for SNLI), where all 5 explanations for a given instance are placed in the same set to avoid leakage. We present statistics on the label distribution in Table 6. Along with the metric settings reported in the paper (“select-1” and explanation-level), we computed a metric that is instance-level but considers all explanations by computing metrics over the 5 explanations of an instance and then averaging across instances, finding in practice that the results are highly similar to the explanation-level evaluation.

We use Huggingface Datasets (Lhoest et al., 2021) and Huggingface Transformers (Wolf et al., 2020) for implementation. The T5-Large model is trained using a learning rate of $1E−4$ with linear decay, a batch size of 64, and default values for Adam (Kingma and Ba, 2015), gradient clipping,
and dropout. We train for a maximum 200 epochs, performing early stopping on the validation loss with a patience of 10 epochs.

For T0-3B, we train with a batch size of 50. We use AdaFactor \cite{ShazeerS18} with a linear warmup of 500 steps. We conduct an initial hyperparameter sweep over learning rate, considering $1E - 5, 5E - 05, 5E - 06$. The learning rate that achieves the best validation loss for the full-information model and the explanation-only model is $1E - 5$, which we use for all training experiments. We format inputs to the model as follows:

```python
if explanation_only:
    input_string = (f"explanation: {expl}. 
    Is this explanation good or bad?"
else:
    input_string = ( 
    "{question} answer: {gold_label}. 
    "explanation: {expl}. 
    Is this explanation good or bad?"

For CommonsenseQA, question, expl, and gold_label are: the commonsense QA question (with answer options omitted), the explanation candidate from GPT-3, and the true answer among the 5 options, respectively; for SNLI, premise: ... hypothesis: ..., the explanation candidate from GPT-3, and one of entailment/contradiction/neutral, respectively.

E Additional Filter Results

In the main experiments, at evaluation time, we labelled an explanation as acceptable if 3/3 annotators agreed on it. Here, we report results if this threshold is relaxed to 2/3. Overall, the results are comparable: T0-3B outperforms the baselines according to both select-1 accuracy and AP (see Table 17 and Table 18).
| AMT Study                                                                 | Task/Dataset       | # Annotators | Median # HITs (Mean) |
|--------------------------------------------------------------------------|--------------------|--------------|---------------------|
| GPT-3 Greedy: Our Handwritten vs. Dataset Prompts                        | Com.QA/CoS-E       | 7            | 84 (107.14)         |
|                                                                           | Com.QA/ECQA        | 13           | 49 (57.69)          |
|                                                                           | e-SNLI             | 8            | 43.5 (93.75)        |
| GPT-3 Greedy vs. Dataset                                                 | Com.QA/CoS-E       | 8            | 90 (93.75)          |
|                                                                           | Com.QA/ECQA        | 17           | 27 (44.12)          |
|                                                                           | e-SNLI             | 8            | 93 (93.75)          |
| GPT-3 Greedy (Absolute)                                                  | Com.QA             | 13           | 51 (57.69)          |
|                                                                           | SNLI               | 12           | 14 (62.5)           |
| Dataset (Absolute)                                                       | CoS-E              | 14           | 58 (53.57)          |
|                                                                           | ECQA               | 19           | 7 (39.47)           |
|                                                                           | e-SNLI             | 13           | 16 (57.69)          |
| Acceptability (Training and Validation Data)                             | Com.QA (2973 HITs) | 34           | 70 (87.44)          |
|                                                                           | SNLI (3000 HITs)   | 14           | 128.5 (214.29)      |
| Acceptability (Test Data)                                                | Com.QA             | 17           | 32 (44.12)          |
|                                                                           | SNLI               | 11           | 26 (68.09)          |
|                                                                           | SNLI (Test_Crowd2) | 7            | 65 (107.14)         |

Table 13: Total # of annotators and mean # HITs completed per-annotator for each AMT study (out of 750 total # HITs unless otherwise specified = 3 annotators for each of 250 test instances).

| AMT Study                                                                 | Dataset            | Krippendorff’s α |
|--------------------------------------------------------------------------|--------------------|------------------|
| GPT-3 Greedy: Expert-Written vs. Dataset Prompts                        | Com.QA/CoS-E       | 0.16             |
|                                                                           | Com.QA/ECQA        | 0.30             |
|                                                                           | e-SNLI             | 0.47             |
| GPT-3 Greedy vs. Dataset                                                 | Com.QA/CoS-E       | 0.46             |
|                                                                           | Com.QA/ECQA        | 0.43             |
|                                                                           | e-SNLI             | 0.22             |
| Acceptability (Training Data)                                            | Com.QA             | 0.32             |
|                                                                           | SNLI               | 0.51             |
| Acceptability (Test Data)                                                | Com.QA             | 0.40             |
|                                                                           | SNLI               | 0.50             |
|                                                                           | SNLI (Test_Crowd2) | 0.47             |

Table 14: Inter-annotator agreement for course-grained (head-to-head and acceptability) AMT studies. Krippendorff’s α is computed on an interval scale based on the 5-point Likert scale for the head-to-head studies and on a binary scale for the acceptability task.

| AMT Study                                                                 | Dataset     | Generality | Factuality | Grammar | New Info | Supports Label | Amount Info |
|--------------------------------------------------------------------------|-------------|------------|------------|---------|----------|----------------|-------------|
| GPT-3 Greedy Dataset                                                    | CoS-E       | 0.37       | 0.32       | -0.01   | 0.09     | 0.45           | 0.21        |
| GPT-3 Greedy Dataset                                                    | ECQA        | 0.71       | 0.38       | 0.36    | 0.42     | 0.68           | 0.08        |
| GPT-3 Greedy Dataset                                                    | SNLI        | 0.01       | 0.21       | 0.30    | 0.00     | 0.03           | 0.25        |
| GPT-3 Greedy Dataset                                                    | e-SNLI      | 0.25       | 0.57       | 0.39    | -0.01    | 0.04           | 0.17        |
| GPT-3 Greedy Dataset                                                    | Com.QA      | 0.37       | 0.23       | 0.37    | -0.14    | -0.12          | 0.04        |

Table 15: Inter-annotator agreement for absolute-comparison AMT studies, using Krippendorff’s α computed on an interval scale from -1 to 1 (see coding in Table 5).
“Supports Label” was always answered instead of being conditioned on “New Info”.

Table 16: Statistics from the graphs plotted in Figure 2. Mean ± standard error presented; numbers in parenthesis indicate the number of datapoints, if not 250. *For SNLI, we modified the evaluation framework such that “Supports Label” was always answered instead of being conditioned on “New Info”.

| Set of Test Explanations | Generality | Factuality | Grammar | New Info | Supports Label | Amount Info |
|--------------------------|------------|------------|---------|----------|---------------|-------------|
| GPT-3 Greedy for Com.QA  | 0.9 ± 0.4  | 0.8 ± 0.3 (237) | 1.0 ± 0.1 | 0.1 ± 0.6 | 0.5 ± 0.7 (166) | 0.0 ± 0.4 (113) |
| CoS-E                    | −0.2 ± 0.9 | 0.6 ± 0.5 (108) | −0.3 ± 0.7 | 0.1 ± 0.8 | −0.3 ± 0.8 (149) | −0.5 ± 0.3 (42) |
| ECQA                     | 0.8 ± 0.4  | 0.6 ± 0.4 (242) | 0.1 ± 0.7 | 0.6 ± 0.5 | 0.7 ± 0.5 (219) | 0.4 ± 0.5 (174) |
| GPT-3 Greedy for SNLI    | 0.7 ± 0.5  | 0.7 ± 0.5 (226) | 1.0 ± 0.2 | 0.1 ± 0.6 | −0.1 ± 0.6* | −0.1 ± 0.3 (128) |
| e-SNLI                   | 0.6 ± 0.6  | 0.8 ± 0.4 (213) | 0.9 ± 0.4 | 0.2 ± 0.5 | 0.2 ± 0.5* | −0.1 ± 0.3 (185) |

Table 17: Results for acceptability classifiers trained on CommonsenseQA, with “acceptability” defined as: “at least 2/3 annotators labelled as acceptable.” Subscripts indicate standard error over models trained with 5 different random seeds.

| Model/Split →          | “Select-1” Acc@2/3 | Explanation-level AP@2/3 |
|------------------------|-------------------|--------------------------|
|                        | Dev               | Test | Dev         | Test        |
| Random                 | 57.3±0.4          | 57.9±0.4 | 56.2±0.5 | 58.0±0.9   |
| Constant               | —                 | —   | 56.9       | 58.0        |
| NLL                    | 79.1              | 79.6 | 77.5       | 75.0        |
| T0-3B Expl.-only       | 77.1±3.5          | 75.8±1.2 | 75.6±2.0 | 77.3±1.4   |
| T0-3B                  | 86.6±0.9          | 85.8±0.7 | 85.6±0.5 | 87.0±0.8   |
| Oracle Upper-Bound     | 97.8              | 97.6  | 100.0     | 100.0       |

Table 18: Results for acceptability classifiers trained on SNLI with “acceptability” defined as: “at least 2/3 annotators labelled as acceptable.” Subscripts indicate standard error over models trained with 5 different random seeds.

| Model/Split →          | “Select-1” Acc@2/3 | Explanation-level AP@2/3 |
|------------------------|-------------------|--------------------------|
|                        | Dev               | Test | Test_Crowd2 | Dev         | Test | Test_Crowd2 |
| Random                 | 28.2±0.5          | 27.8±0.2 | 28.0±1   | 28.1±0.9 | 27.6±0.3 | 28.3±0.6 |
| Constant               | —                 | —   | —          | 28.2       | 27.8    | 28.0      |
| NLL                    | 51.0              | 51.2  | 50.4       | 47.7       | 47.5    | 46.1      |
| T0-3B Expl.-only       | 47.0±1.0          | 50.5±2.1 | 50.6±2.8 | 48.9±1.4 | 45.2±1.5 | 44.9±2.1 |
| T0-3B                  | 57.8±1.9          | 60.3±1.5 | 59.2±3   | 66.7±3.3 | 64.7±3.3 | 67.1±3.6 |
| Oracle Upper-Bound     | 76.0              | 81.2   | 77.6       | 100.0     | 100.0   | 100.0     |
Figure 3: An overview of the user interface of our head-to-head comparison AMT studies for CommonsenseQA. The top shows the instructions and the bottom the actual task. The Examples tab is collapsed here; shown in full in Figure 4.
Figure 4: The Examples tab given in the user interface of our head-to-head comparison AMT studies for Common-senseQA. The full interface is shown in Figure 3.
Figure 5: An overview of the user interface template of our absolute comparison AMT studies for Common-senseQA. The top shows the instructions and the bottom the actual task. Only part 1 of the task is shown here (part 2 appears once part 1 is submitted). The Main Example and More Examples tabs illustrating both parts 1 and 2 are collapsed here; see Figure 6.
Main Example (click to expand/collapse)

Part 1: Please read the below statement and answer the following questions:

**people keep furniture, such as lanterns, at their houses for personal use in their daily living.**

1) How factual is this statement?
- Generally False
- Sometimes or Partially True
- Generally True
- Need More Information to Judge

This statement is **Generally True**.

2) Is this statement grammatical?
- No
- Yes

The correct answer is **Yes**.

Part 2: Please read the instance that the statement explains and answer the following questions:

**Question:** If a lantern is not for sale, where is it likely to be?
**Answer:** house
**Explanation:** people keep furniture, such as lanterns, at their houses for personal use in their daily living.

3) Does the **Explanation** provide new facts, information, or reasoning not stated in the **Question** and **Answer**?
- Examples
- Yes

The correct answer is **Yes** because the explanation introduces the fact that lanterns are a type of furniture, and that people do not usually keep furniture in their house for selling.

4) Is the new information relevant to justifying the **Answer**?
- Examples
- Yes

The correct answer is **Yes**.

5) How much information does the **Explanation** have to justify the **Answer**?
- Not Enough
- Enough
- Too Much

The correct answer is **Enough**.

Figure 6: The Main Example given in the user interface template of our absolute comparison AMT studies for CommonsenseQA. This format follows the actual task layout. The full interface is shown in Figure 5.
Figure 7: An overview of the user interface of our explanation acceptability AMT studies for CommonsenseQA. The top shows the instructions and the bottom the actual task. The "examples" tab is collapsed here; shown in full in Figure 8.
Figure 8: The examples given in the user interface of our explanation acceptability AMT studies for Common-senseQA. The full interface is shown in Figure 7.