**CREPE: Open-Domain Question Answering with False Presuppositions**

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**Abstract**

When asking about unfamiliar topics, information seeking users often pose questions with false presuppositions. Most existing question answering (QA) datasets, in contrast, assume all questions have well defined answers. We introduce CREPE, a QA dataset containing a natural distribution of presupposition failures from online information-seeking forums. We find that 25% of questions contain false presuppositions, and provide annotations for these presuppositions and their corrections. Through extensive baseline experiments, we show that adaptations of existing open-domain QA models can find presuppositions moderately well, but struggle when predicting whether a presupposition is factually correct. This is in large part due to difficulty in retrieving relevant evidence passages from a large text corpus. CREPE provides a benchmark to study question answering in the wild, and our analyses provide avenues for future work in better modeling and further studying the task.

**1 Introduction**

When an information-seeking user poses a question about the topic they are unfamiliar with, they can often introduce false presuppositions (Kaplan, 1978; Duži and Čihalová, 2015) which are assumed but not directly stated. For instance, the question in Figure 1 incorrectly presupposes that the equal and opposite reactions in Newton’s law apply to the same object. Although such a question is unanswerable, we might still hope to identify the confusion and explain it to the user. This functionality goes well beyond prior open-domain QA task formulations, which focus on questions with a valid direct answer (Rajpurkar et al., 2016; Kwiatkowski et al., 2019) or that are unanswerable from lack of evidence (Rajpurkar et al., 2018; Choi et al., 2018; Asai and Choi, 2021). While recent work studies unverifiable presuppositions in reading-comprehension-style questions given evidence context (Kim et al., 2021), there has been no work that identifies and corrects a presupposition that is false based on global, factoid knowledge.

In this paper, we introduce CREPE (CorrRection of Presupposition), a new dataset consisting of 8,400 Reddit questions with (1) whether there is any false presuppositions, and (2) if any, the presupposition and its correction written. We find 25% of questions on Reddit (Fan et al., 2019) include false presuppositions, where the best response is to provide a correction of the presuppositions.

While the CREPE annotation task is challenging due to the need for extensive background knowl-
edge and inherent debatability, we leverage the most upvoted comments written by community users to efficiently annotate the data. The most upvoted comments are likely to be factually correct, and typically also identify and correct any false presuppositions made in the question. By designing an annotation pipeline using these comments, we were able to collect high-quality data at a relatively low cost. Our data analysis (Table 2) shows that the types of false presuppositions are diverse, ranging from relatively explicit presuppositions (e.g., false clauses or false predicate) to subtle, nuanced presuppositions (e.g., false causality or false existential presuppositions).

We define two tracks with varying levels of difficulty, and introduce models to set baseline performance levels for each. A model is given either the question only (the main track) or the question and the comment (the GOLD-COMMENT track), and is supposed to perform two subtasks: identification of whether or not there is a false presupposition (the detection subtask) and generation of presuppositions and their corrections (the writing subtask).

For the writing subtask, we propose a systematic human evaluation scheme based on Celikyilmaz et al. (2020) that considers fluency, correctness (precision of the information), adequacy (recall of the information) and consistency.

We include a range of baselines, including a question-only model, a nearest-neighbor model, and a competitive model based on the state-of-the-art passage retrieval (Krishna et al., 2021) and pretrained language models (Liu et al., 2019; Raffel et al., 2020). Results and analyses indicate that (1) retrieval is very challenging since simply retrieving passages in the topic of the question is not enough; (2) models do moderately well in identifying explicit false presuppositions, and (3) models struggle with identifying implicit presuppositions and explaining how and why the presupposition is false. We also discuss open problems, such as an inherent ambiguity in the validity of presuppositions and inconsistency between different websites.

2 Background

2.1 Question Answering

There has been significant work on question answering, where the model receives a natural language, open-domain question and is required to return a short, concise answer (Voorhees and Tice, 2000; Lee et al., 2019). Most work focuses on questions that have a short text span as a correct answer. Other work studies unanswerable questions, but they study questions that are either intentionally written to be unanswerable (Rajpurkar et al., 2018) or where there is a lack of evidence to find the answer (Choi et al., 2018; Asai and Choi, 2021). More recently, Kim et al. (2021) studies unverifiable presuppositions in questions under the given context, but using questions from Kwiatkowski et al. (2019) whose presuppositions are mostly not false based on global knowledge.²

In this work, we focus on open-domain questions with presuppositions that are false based on global knowledge, and argue that an adequate response to them is a correction of these presuppositions. We show that false presuppositions in questions are prevalent. 25% of questions contain false presuppositions in the domain of online forums (for which we collect annotations), research papers (Dasigi et al., 2021), scientific reviews (Kang et al., 2018), and social media (Sap et al., 2020).

2.2 Presupposition

Under a pragmatic point of view, a presupposition is a condition that a speaker would normally expect to hold in the common ground between discourse participants when that sentence is uttered (Beaver et al., 2014; Stalnaker et al., 1977). Unlike semantic presuppositions (Strawson, 1950), pragmatic presuppositions cannot easily be traced to specific words or phrases, but rather depend on the context and the expectations of the discourse participants (Potts, 2015). A key property of pragmatic presuppositions is that they are backgrounded—a pragmatic property of being a meaning that the speaker presumes to be mutual public knowledge. While whether or not one is a presupposition is inherently debatable, we define a false presupposition based on the most voted comment in the online forum, as we discuss further in Section 3.2.

False presuppositions in questions have been discussed in the linguistic literature (Kaplan, 1978; Duží and Čihalová, 2015). False presuppositions in the question make a question infelicitous because there is no direct answer. Kaplan (1978) claims that an adequate and unambiguous answer to such a question is a negated presupposition, referred to as corrective indirect response. We follow them in providing the negated presupposition as the response.

²Less than 5% of questions from Kwiatkowski et al. (2019) contains false presupposition under our definition, likely because their questions are aggressively filtered.
to the question, and build the first benchmark based on questions written by information-seeking users.

3 Dataset: CREPE

Our task requires the model to be given a question \( q \) and to (a) identify whether \( q \) has any false presuppositions, and (b) if yes, generate the false presupposition as well as the correction.

We have three criteria in constructing the dataset:

- **C1.** Naturalness of the questions: whether the questions in the data are written by real, information-seeking users.
- **C2.** Validity of the presupposition: whether the identified presupposition is highly likely made by the question writer.
- **C3.** Correctness and adequacy of the information: whether the information provided in the correction is factually correct, and adequate to convince the question writer.

We first describe the source of questions (Section 3.1) which address C1. We then describe the process of annotation (Section 3.2) that addresses C2 and C3. Finally, we present detailed, qualitative analysis of the data (Section 3.3). The formal definition of the task and metrics are in Section 4.

3.1 Data Source

Our highest priority is to study false presuppositions that naturally occur from information-seeking users. While it is significantly easier to manually write questions that would have false presuppositions, we think these questions will significantly be different from naturally occurring questions.

Following Fan et al. (2019), we use questions posted on the ELI5 subreddit. We made a few modifications to the procedure that Fan et al. (2019) took in order to improve the data quality. We first filter questions and comments based on upvotes with a higher threshold. We then split the training, the development and the test data based on the time of the posting: questions on the training set are posted in 2011–2018, questions on the development set are posted in Jan–Jun of 2019, and questions on the test set are posted in Jul–Dec of 2019. Appendix A provides more details.

Krishna et al. (2021) raised a concern that a significant amount of test are duplicates of those on the training set. We provide a detailed analysis in Appendix A. In summary, we think (1) the amount of duplicated (or paraphrased) questions is significantly less than their estimate with respect to underlying presuppositions in the questions, and (2) even if there are paraphrased questions, data split based on the time frame is justified based on the real-world scenario.

3.2 Data Annotation

Meeting the criteria C2 and C3 can be very difficult for the following reasons:

- For C2: The validity of presupposition is inherently debatable and largely depends on the background of individuals (Section 2.2).
- For C3: The open-domain nature of the task requires the search of world knowledge on the web, which is extremely expensive and may not be exhaustive enough despite the best efforts made by annotators, as discussed in Kwiatkowski et al. (2019); Min et al. (2020).

In this work, we make use of the most upvoted comments written by community users. The comment, often written by domain experts, provides a response to the question in the ELI5 subreddit and has been used as a credible source in prior work (Fan et al., 2019). If the comment identifying a false presupposition has the most upvotes, it is likely that the presupposition is valid (made by a question writer) based on the background context shared by community users, thus satisfying C2. Moreover, the comment (1) is highly likely to contain information that is correct and adequate (satisfying C3), and (2) removes the need for exhaustively searching over the web (reducing the annotation cost).

Annotation task. Annotators are given a pair of the question and the most voted comment, and perform the following steps.

1. Filter out questions that are subjective, are uninformative, or rely on personal experience.
2. Judge whether there is a false presupposition in the question, identified by the comment.
3. If there is a false presupposition, write the presupposition and a correction as a concise, declarative sentence.

\(^4\)We think having similar questions is an inherent property of questions on the web, and the model should be allowed to take whichever approach that is plausible, including the nearest neighbor approach (Lewis et al., 2021).

\(^5\)This is also the case in previous work—for instance, the data annotated by experts in formal semantics and pragmatics can have low agreement (Jeretic et al., 2020).
| Data split    | # Questions | # Tokens | Posting time |
|--------------|-------------|----------|-------------|
|              | Tot w/ FP   | Q PS CR CM |             |
| Training     | 3,462 907 (26.2%) | 15.6 10.3 16.5 95.2 | 2018        |
| Development  | 2,000 544 (27.2%) | 16.1 10.3 15.6 91.0 | Jan–Jun 2019 |
| Test         | 3,004 751 (25.0%) | 16.4 11.8 16.8 92.5 | Jul–Dec 2019 |
| Unlabeled training | 196,385 | - 15.7 - 96.6 | 2011–2018 |
| Total (labeled only) | 8,466 2,202 (26.0%) | 16.0 10.8 16.5 93.3 |             |
| Total (labeled+unlabeled) | 204,851 | - 15.7 - 96.5 |             |

Table 1: Data statistics. # Questions indicate the number of questions in total and with false presupposition. # Tokens indicate the number of tokens (based on the whitespace tokenization) in the question (Q), the presupposition (PS), the correction (CR), and the comment (CM). Note that PS and CR are those to be written by the model; CM is given to the model in the GOLD-COMMENT track. Details of tracks are provided in Section 4.

Annotation pipeline. We maintain a pool of qualified annotators who passed our qualification task. We assign two annotators per question, where each annotators independently annotate the question. We filter out questions if either of the annotators mark them as such. If the annotators agreed to on the label (whether or not there is a false presupposition), their label as well as their writings are taken as gold references. When they disagreed, we assign a third annotator and take a majority vote over three workers. The percentage agreement in the initial stage of the annotation is 75%, and the Fleiss’ kappa is 43%, indicating moderate agreement.\(^6\) We find that the disagreements are mainly due to inherent ambiguities of the task due to the different interpretations of the question or the comment, or difference in individual background knowledge (discussion in Section 3.3).

More details in instructions and quality control are provided in Appendix B.

3.3 Data Analysis

The data statistics are provided in Table 1. We find that over 25% of questions posted on Reddit includes false presuppositions.\(^7\)

Categorization of false presuppositions. We randomly sample 50 questions with false presuppositions and categorize them in Table 2. The five most frequent types of presuppositions include:

- **False clauses** are those where FP is made as a clause in Q, e.g., “the water has to be 100 to become steam” in Table 2.
- **False predicate** are those where the predicate in Q is false, e.g., “current is stored in power plants”.
- **False properties** are those where certain properties or attributes are presupposed in Q, e.g., “cement blocks are too strong so that people who punch them are likely to break their hand.” They are often very implicit and may be deniable; however, the question writer would not have asked the question if they have not made the presupposition.
- **False (causal) relationship between facts** are those where Q makes a (causal) relationship between facts that are false. This is another implicit type of presuppositions, but again, the question writer would not have asked this question if they have not made such a presupposition. A large portion of questions involve scientific phenomenon on which the question writer has misunderstanding, e.g., in the example in Table 2, the question writer had a misconception about Newton’s Third Law of Motion.
- **False existential presupposition** indicates that Q includes an existential presupposition, one type of semantic presuppositions, that is false. For instance, the example Q in Table 2 presupposes an unused space in a hard disk, and C says there is no unused space.

Triggers in the comment. We analyze how comments point out the falsehood of the presupposition made in the question on the same set of 50 samples on the development data. In 68% of times, comments include specific lexical cues which we call triggers. 70% of such triggers are negations. Other word-level triggers include “actually”, “just”, “rare”, “really” and “though”. Sentence-level triggers include “You are mistaken”, “You’ve got some
False clauses (14%)
Q If water has to be 100 to become steam, how come you don’t get heavily burned in saunas?
C What we often call steam is just water vapor that has started to become visible due to different temperatures of the water vs air. It can exist at many temperatures. (...) FP Water can steam below 100 degrees.

False properties (22%)
Q How do martial artists who karate chop or punch a cement block not break their hand? C It’s a trick, the blocks are not very strong, and they are being punched or kicked in their weakest points. FP Chops or cement blocks are strong.
Q How does your phone tell the difference between a step and random movement? C You might be disappointed by this answer, but most of the time, you’re not moving your phone (...) when you walk. FP A random movement is detectable by a phone.

False existential presupposition (6%)
Q What uses the space on a hard disk that we’re unable to use? For example in a 1TB hard disk, we get about 930GB of usable memory, what happens to the other 70GB?
C There are TB (terabyte) and TiB (tebibyte), the "ra" ones are using multiples of 1000. The "bi" ones are using multiples of 1024. I will do some math for you: 1 TB = 1000^3 B = (...) = 0.93 TiB. There goes your 70 GB.
FP In a 1TB hard disk, 70GB is unusable.

Table 2: Breakdown of types of false presuppositions, based on 50 random samples on the development data. Q, C and FP indicate the question, the comment, and the presupposition, respectively.

Analysis of ambiguous cases. Even with our best efforts, there are still inherent disagreement between annotators. Some of them are due to inherent ambiguities in language, e.g., the first example in Table 9 where ‘the state of the water’ could either mean the molecule itself or the energy state of the molecule. Others are due to disagreement on the validity of the presupposition, e.g., in the second example in Table 9, it is debatable whether or not the question writer presupposes that the Board deals with day to day at a company. We revisit this issue in human performance estimation in Section 5.2.

4 Task Setup
The model is given a question \( q \), and is required to perform the following subtasks:
(a) Detection: assign a label to be FP or N; FP means \( q \) has a false presupposition, and \( N \) means \( q \) has no false presuppositions. We use a macro-F1 score as an evaluation metric.
(b) Writing: if FP, write the false presupposition as well as the correction. We use sacreBLEU (Post, 2018) and unigram-F1 following Petroni et al. (2021) as well as SentBERT (Reimers and Gurevych, 2019) for evaluation. We also introduce a human evaluation scheme in Section 6.3.

We have two tracks: the main track and the GOLD-COMMENT track.

The main track provides \( q \) as the only input to the model. The model is expected to search necessary background knowledge to perform the task from any information source except for Reddit and Quora.\(^8\) This is the most realistic setting for the typical open-domain question answering problem.

The GOLD-COMMENT track provides the comment used for the annotation as an additional input to the model. This removes the need for retrieval, and guarantees that all necessary information to perform the task is given.

\(^8\)This is because similar questions are being asked on these websites. The same decision has made in Nakano et al. (2021).
5 Experiments: Detection

This section discusses baseline experiments for the detection subtask; Section 6 discusses baseline experiments for the writing subtask.

5.1 Baselines

5.1.1 Trivial baselines

Random assigns FP or N randomly at uniform. FP only always assigns FP. N only always assigns N. Nearest Neighbor retrieves one of questions from the training set that is closest to the test question, based on c-REALM (Krishna et al., 2021), and returns its label as the prediction.

5.1.2 GOLD-COMMENT track baselines

Question only trains a RoBERTa-based (Liu et al., 2019) classifier that takes the question as the only input and classifies the label. It is often called closed-book model (Roberts et al., 2020). Comment only is a classifier based on RoBERTa-large that takes the comment as the only input and assigns the label. Question+Comment is a classifier based on RoBERTa-large that takes a concatenation of the question and the comment to the classifier, and assigns the label. We additionally experiment with the same model that is trained on either MNLI (Williams et al., 2018) or BoolQ (Clark et al., 2019), and tested on CREPE in a zero-shot fashion. This condition tests if training on similar, previously studied datasets helps.

5.1.3 Main track baselines

We design a model called c-REALM + MP (Multi-passage) classifier that retrieves a set of paragraphs from Wikipedia and then assigns a label.

First, the model uses c-REALM (Krishna et al., 2021), a state-of-the-art retrieval model on ELI5, to retrieve a set of $k$ passages from the English Wikipedia. Next, the model uses the multi-passage classifier based on RoBERTa in order to assign a label. Given a question $q$ and a set of passages $p_1 ... p_k$, each $p_i$ $(1 \leq i \leq k)$ is concatenated with $q$ and is transformed into $h_i \in \mathbb{R}^k$ through the Transformer model. We then obtain logits via $p = \text{FFN}(\text{MaxPool}(h_1 ... h_k)) \in \mathbb{R}^2$, where FFN is a feed-forward layer and MaxPool is an element-wise max operator. Finally, we use $\text{Softmax}(p)$ to compute the likelihood of $q$ having false presuppositions or not.

Self-labeling. Although our labeled data is small, there is large-scale unlabeled data (question and comment pairs) available. We explore self-labeling to leverage this unlabeled data. Specifically, we use the Question+Comment to assign a silver label to the unlabeled training questions. We then train the classifier on the union of this silver data as well as the gold labeled data.

5.1.4 Human performance

We estimate human performance to better understand the model performance. We recruit two human workers who perform the task for 186 questions for each track.

We estimate two types of human performance. (1) Human with the most voted comment, where human workers assume the most voted comment as a ground truth in terms of factuality of the information and the validity of the presupposition. We think of it as an upperbound of model performance. (2) Human w/o the most voted comment, where human workers search over the web (except Quora and Reddit) to find information, and make the best judgment about the validity of the presupposition. We think it is likely to be worse than the upperbound of model performance, since only one worker, instead of multiple online users or domain experts, makes a decision.

5.2 Results

Results are reported in Table 3.

The GOLD-COMMENT track. All trivial baselines achieve poor performance. In particular, poor performance of the nearest neighbor model indicates that there is no significant train-test overlap on CREPE. Using both the question and the comment (Question+Comment) achieves the best performance, outperforming the best trivial baseline by 22% absolute. Zero-shot models trained on MNLI and BoolQ achieve poor performance, indicating that our problem is significantly different from existing tasks like NLI or binary question answering. The best model is 10% below human performance, indicating room for improvement, even in the easier track.

The main track. Using retrieved passages from c-REALM and multi-passage classifier achieves 66.3% on the test set, which is significantly better than all trivial baselines. The self-labeling technique leads to additional improvements, leading to an F1 of 67.1%. While these numbers are significantly better than trivial baselines, they are significantly worse than the model performance given
Table 3: Baseline results in the detection subtask on the development data and the test data, respectively. Macro-F1 scores reported. By default, the models are trained on the labeled portion of CREPE; ⊗ indicates the model is not trained on CREPE; † indicates the model is trained on both the labeled and unlabeled portions of CREPE.

| Model | Dev   | Test  |
|-------|-------|-------|
| **Trivial baselines** |       |       |
| Random⊗ | 44.9  | 47.8  |
| Always predict FP⊗ | 21.4  | 20.0  |
| Always predict N⊗ | 42.1  | 42.9  |
| Nearest Neighbor⊗ | 56.2  | 54.1  |
| **GOLD-COMMENT track** |       |       |
| Question only | 67.7  | 66.9  |
| Comment only | 68.9  | 68.6  |
| Question⊕Comment | 76.3  | 75.6  |
| Question⊕Comment (MNLI)⊗ | 54.4  | 54.2  |
| Question⊕Comment (BoolQ)⊗ | 60.4  | 58.2  |
| **Main track** |       |       |
| c-REALM + MP classifier | 68.3  | 66.3  |
| c-REALM + MP classifier (Self-labeling)† | 69.1  | 67.1  |
| Human w/ most-voted comment | 86.4  | 85.1  |
| Human w/o most-voted comment | 70.9  | 70.9  |

Table 4: Analysis of 44 errors made by human performers without the most upvoted comment.

| Error Category | %    |
|----------------|------|
| Failure in finding evidence | 11.4 |
| Mistakes in labeling | 11.4 |
| Wrong ground truth label | 11.4 |
| Inherent disagreement: ambiguity | 34.1 |
| Inherent disagreement: criticalness | 9.1 |
| Information on the web being inconsistent | 22.7 |

Table 3: Baseline results in the detection subtask on the development data and the test data, respectively. Macro-F1 scores reported. By default, the models are trained on the labeled portion of CREPE. ⊗ indicates the model is not trained on CREPE; † indicates the model is trained on both the labeled and unlabeled portions of CREPE.

the comment. This strongly suggests a retrieval bottleneck—getting passages that provide evidence as strong as human-written comments is difficult even with the state-of-the-art retrieval model.

To further support the bottleneck in retrieval, we conduct a detailed error analysis in Appendix C.2. For instance, 86% of false negatives were due to retrieval misses, including failing to retrieve relevant topics (42%), retrieving evidence on the relevant topics but not related to the false presuppositions (32%), or retrieving evidence related to the presuppositions but is not direct enough (12%).

**Human performance.** Humans given the most upvoted comment achieve performance that is significantly higher than all baseline numbers, indicating significant room for improvement.

Without the most upvoted comment, people achieve relatively poor performance (70.9%). To better understand this, we analyze 44 error cases, and categorize them in Table 4. Nearly half of the errors are due to an inherent disagreement in labels, either due to (1) ambiguity, either in language or whether the presupposition was made, or (2) whether it is critical to correct false presuppositions (especially cases in the exception category in Table 2). We think using the most upvoted comment for a decision is reasonable since it is an aggregation of active community users and domain experts, but future work may take other approaches to consider ambiguities of the decision.

6 Experiments: Writing

6.1 Baselines

In the writing subtask, the system is given a question that is guaranteed to contain a false presupposition, and is required to generate the presupposition as well as the correction.

6.1.1 GOLD-COMMENT track baselines

**Copy baseline.** As a trivial baseline, we copy the given question as a presupposition and the given comment as a correction.

**Question⊕Comment Dedicated.** We train two generators separately to generate the presupposition and the correction, respectively, given a concatenation of the question and the comment. Both models are based on the pretrained T5-base model (Raffel et al., 2020).

**Question⊕Comment Unified.** We also design a unified model that can be used for both the presupposition and the correction, motivated by the intuition that generation of each can benefit from each other. We train one generator that is trained with a union of (1) annotated corrections, and (2) annotated presuppositions prepended with “It is not the case that” so that they look like corrections. At inference time, we use a standard, beam search decoding to generate the correction. To generate the presupposition, we first decode a sequence with a constraint (De Cao et al., 2021) that it should start with “It is not the case that”, and then take the sequence that comes next as a presupposition.

6.1.2 Main track baselines

We design c-REALM + MP (Multi-Passage) Dedicated and c-REALM + MP (Multi-Passage) Unified. They are similar to the dedicated and unified...
models in Section 6.1.1. The only difference is that the model receives a question and a set of k passages from c-REALM instead of a question-comment pair. In order for the T5 model to read multiple passages, we use the Fusion-in-Decoder architecture (Izacard and Grave, 2021). We refer to Appendix C.1 for more details.

### 6.2 Results: Automatic Evaluation

Table 5 reports the results in unigram F1 and BLEU. Examples of model outputs are provided in Appendix C.4. All models outperform the trivial copy baseline and perform better in the GOLD-COMMENT track than in the main track. Models are overall better at writing presuppositions than writing corrections, and the performance gap between the GOLD-COMMENT track and the main track is larger in presuppositions than in corrections. This is likely because the impact of evidence passages is more significant in correction writing than in presupposition writing since the presupposition can often be extracted from the question alone, while the correction requires information beyond the question. It is also worth noting that the unified model is better than the dedicated model in the main track but not in the GOLD-COMMENT track. This indicates that, while multi-task learning improves the main track, it does not improve the GOLD-COMMENT track, possibly because performing two tasks in isolation is sufficient.

Table 6 reports results in SentBERT scores. The overall scores are high, likely because SentBERT considers entailment between a reference and a generation. For instance, the copy baseline achieves high scores since the question and the presupposition, and the comment and the correction entail each other by definition. It is important to note that entailment is a necessary but not a sufficient condition for a presupposition or a correction to be satisfactory in our task definition. The next section shows that models with high SentBERT scores obtain low human ratings.

### 6.3 Results: Human Evaluation

We conduct human evaluation of model generations on 200 randomly sampled test instances from the...
following aspects (each in the 0–3 scale):

- **Fluency**: The generated text should be fluent (i.e., free of grammatical errors, spelling errors, and repetitions).
- **Presupposition**: The generated presupposition should be the valid one in the question, and is factually false.
- **Correction**: The correction should be made in the comment and provide reasonable amount of justification rather than being a simple negation of the presupposition.
- **Consistency**: The presupposition and correction should be on the same topic and negate each other.

We evaluate the output from all systems except the copying baseline, as well as the ground truth reference. Each question is assigned two raters in order to reduce noise and report inter-rater agreement on pairwise comparison. More details about the rating scheme are provided in Appendix C.4.

Based on results reported in Table 7, all models generate almost flawless fluent text and valid presuppositions. However, their outputs generated as false presuppositions are factually correct in half of the cases. These observations are relatively consistent across different systems.

Notable differences between systems are found in correction and consistency. The dedicated model generates better correction, likely because it is given a comment. All other models struggle: in particular, the unified models tend to generate the correction that starts with “It is not the case that” even the model is not restricted to do so at inference time. On the other hand, the unified model is better in consistency, likely because the dedicated model is more vulnerable in generating the presupposition and the correction in a totally different topic.

### 7 Conclusion

We introduced CRePE: the first benchmark for the identification and correction of false presuppositions in the open-domain setup. CRePE consists of 8,400 user questions, 25% of which contain false presuppositions and are paired with their corrections. Our detailed analysis highlights challenges in solving the task, including (1) retrieval of evidence that identifies false presupposition, (2) identification of implicit and subtle presuppositions, and (3) generating correction that is accurate and adequately explains how and why the presupposition is false. We hope our benchmark adds to the problem of open-domain, open-ended question answering, inviting researchers to build models to study questions with false presuppositions. Further, we suggest future work to develop better models, explore approaches to address inherent debatability of the judgment, and evaluation of the model generation.

### Limitations

**Inherent debatability in false presuppositions.** As discussed earlier, the validity of presupposition is inherently debatable and largely depends on the background context, i.e., even experts in formal semantics and pragmatics observe a high disagreement rate (Jeretic et al., 2020). Our proposal in using the most upvoted comments partially address the issue, but not perfectly, as discussed extensively in Section 5.2. One avenue for future work is to consider extra-linguistic context such as individuals background when judging the validity of presuppositions (Zhang and Choi, 2021).

**Evaluating massive language models.** Massive language models such as GPT-3 (Brown et al., 2020) have been shown impressive performance in open-ended question answering (Nakano et al., 2021). Our paper does not include large-scale, systematic evaluation of such models. Instead, we conduct a small-scale case study with GPT-3 text-davinci-002. See Appendix D for details. Most generations are roughly on the right topic, but often contain information that is factually false and do not precisely answer the question. Moreover, they rarely explicitly identify false presupposition and provide corrections, indicating that GPT-3 is far from solving our task. We think future work may explore larger-scale evaluation in a more systematic manner.

**False presuppositions beyond online forums.** The domain of CRePE is limited to online forums (Reddit). While this choice was made due to the availability of large data and its general domain, we argue that false presuppositions are not specific to such domains. For instance, we find that a similar portion (25%) have false presuppositions on information-seeking questions on NLP research papers posed by NLP experts; see Appendix E for details. We think future work can explore creating benchmarks on such domains, as well as studying
false presuppositions on a broader set of domains that require domain expertise.

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A Details in Data Source

License. The ELI5 (Fan et al., 2019) dataset uses the BSD License. Our usage of this dataset is consistent with its intended use, and the license will be included when downloading the data.

Filtering Data Sources. When the question has several comments, we choose the comment with the highest upvotes. Since our data is derived from Reddit, it may contain unintended social bias or harmful content. To remove toxic language on the data, we follow the toxicity word list from Cachola et al. (2018) to remove questions that contain any of the toxic words, except “hell” and “damn”, as these two words are commonly used as interjections. The original authors of the ELI5 dataset (Fan et al., 2019) and we have made our best efforts to remove such content; however, it is possible that some harmful context may remain on the data after the filtering process.

Analysis in Train-Test Overlap. Krishna et al. (2021) reported that 81% of the validation questions of the original ELI5 dataset are paraphrases of the question on the training set. We revisit this issue, and show with a careful assessment of underlying assumptions and a finer-grained definition of “paraphrases”, the proportion of paraphrased questions is significantly smaller.

We assess 104 randomly sampled questions in the validation set with their closest 7 training questions retrieved using c-REALM, as Krishna et al. (2021) did, but with a different rating scale (1–4), following Bhagat and Hovy (2013), Ganitkevitch et al. (2013), and Pavlick et al. (2015):

1. No Paraphrase; No similar intention: Two questions do not share the meaning nor the intention.
2. No Paraphrase; Similar intention: Two questions are likely to have the same intention, but they are not paraphrases, because their literal meanings are different and/or their underlying assumptions are different.
3. Non-trivial paraphrase: Most of the two questions’ meanings are the same; however, they do not belong to any of lexical paraphrase (single word to single word), phrasal paraphrase (multiword to single/multiword), or syntactic paraphrase (paraphrase rules containing non-terminal symbols), and require non-trivial background knowledge to identify whether they have the same meaning.
4. Paraphrases: Two questions fall into either lexical paraphrase, phrasal paraphrase, syntactic paraphrase, structured paraphrase, or other trivial paraphrase.

Table 8 presents the percentage and an example of each category. 76.9% questions have a rating of 2 or less, indicating that for most validation question, there are either no similar intention question in the training set, or there are questions with similar intention but either their literal meanings are different or their underlying assumptions are different. In particular, the latter indicates that whether or not there is a false presupposition can be different, even though they may share similar intention. Only 23.1% questions have a rating of 3 and above, indicating that relatively few questions in the validation set have a non-trivial or trivial paraphrase in the training set.

We also explored automatically filtering paraphrased questions using BLEU or TF-IDF. However, we find it is non-trivial to find the right threshold, thus include all questions and leave filtering to future work.

B Details in Data Annotation

The annotation instruction is in Figure 2, and we show an example of the annotation interface in Figure 3. The data collection is approved by an Institutional Review Board.

Qualification Task. The qualification task contains 20 pre-annotated questions by the authors, and we provide examples as well as their explanation to workers to demonstrate our task. Based on both whether the worker can correctly identify false presupposition and the writing quality, we selected 30 qualified workers.

Generation Task. Qualified workers who passed the qualification task work on the main annotation task. Each question is assigned to two generators who independently annotate the label. We monitor the agreement of workers and send the disagreed cases to further validate. We revoke qualification of generators whose more than 10% of annotations marked to be invalid by the validators.

Validation Task. If two generators disagree on the label, their annotations are sent to two validators who judge their validity. We select a smaller
1 (45.2%)  
**Dev:** Why are aluminium alloys difficult to weld?  
**Train:** Cold welding. Two pieces of metal touch in a vacuum, why do they stick together? How strong is this weld?

2 (31.7%)  
**Dev:** How is blood after a transfusion integrated into the body, especially when the transfused RBCs carry different DNA than the host RBCs?  
**Train:** How DNA from blood is changed when getting a blood transfusion.  
**Comment:** The dev question assumes that the transfused RBCs carry DNA, while the train question does not.

3 (6.7%)  
**Dev:** How is information retained in solid-state memory devices after power is turned off?  
**Train:** How do electronics keep memory after you take all power sources away?  
**Comment:** It is not trivial that “information retained in solid-state memory devices” is a paraphrase with “electronics keep memory”.

4 (16.3%)  
**Dev:** What is the difference between centrifugal and centripetal force?  
**Train:** The difference between centrifugal force and centripetal force.

Table 8: The rating scale for paraphrase and examples for each category.

Table 9: Two types of ambiguous cases. Q and C indicate the question and the comment, respectively.

we use the top-5 passages as the context and a per GPU batch size of 8. We train all our model with learning rate $10^{-5}$, weight decay of 0, and maximum sequence length of 256. We train all our models for 5000 steps and a gradient accumulation step of 5. We run the classifier models with 5 different random seeds and report the best result.

All experiments were done with two Nvidia-RTX6000 GPUs (the detection subtask) or two Nvidia-A40 GPUs (the writing subtask). We use half-precision training (Micikevicius et al., 2018) when training for our detection task and gradient checkpointing from fairscale (authors, 2021), and choose the best checkpoint based on the performance on the validation set and report its test set performance. For the unified models for the writing subtask, we choose the best checkpoint that gives the best BLEU score for presupposition.

C.2 Error analysis on the detection subtask  
We conduct error analysis of predictions from c-REALM + MP classifier in the detection subtask. The authors annotate 50 false positive instances and 50 false negative instances on the validation set, sampled uniformly at random, and categorize the cause of errors.

Results are reported in in Table 10. Overall, most errors are due to failure in retrieval—although the model often successfully retrieves passages that are on right topic, it fails to retrieve passages that contain enough information about whether the backgrounded presuppositions are true or false. This issue is more prominent in false negatives, likely because finding that the presupposition is true requires significantly more exhaustive search than

| Table 9: Two types of ambiguous cases. Q and C indicate the question and the comment, respectively. |
|-------------------------------------------------|

| Ambiguity in language              | Question                                                                 | Comment                                                                 |
|------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------------|
| Q When water boils, its bubbles are round, but when it freezes, its crystals are 6-sided. Why isn’t frozen water round or boiling water hexagonally shaped? Aren’t H2O molecules the same in either state? | C Bubbles are round because (…) Ice crystals are shaped in such a way because (…) The water molecules are much slower and aren’t bouncing all over the place. Gaseous H2O is much higher energy and further apart so that the regular pattern of ice doesn’t come into effect. |
Why aren’t helicopters used to rescue hikers and remove bodies from Mt. Everest?
- The air in too thin and they can’t fly that high up. They create lift by pushing air downwards. The higher up you go, the less air pressure you have, the less downward force a helicopter can make to fight gravity.

Retrieved Passage: In 2016 the increased use of helicopters was noted for increased efficiency and for hauling material over the deadly Khumbu icefall. In particular it was noted that flights saved icefall porters 80 trips but still increased commercial activity at Everest.

Original Label: No FP.
Model Prediction: FP.

Comment: Helicopter is used to rescue people from Mt. Everest according to the passages, but the comment does not point this FP out.

How does alcohol effect blood sugar in people with Diabetes?
- Short answer: straight alcohol doesn’t affect me at all (vodka, whiskey, etc). I can drink without any noticeable effect on my blood sugar levels (and I have a continuous glucose monitor so I can literally see the effect or lack thereof)...

Retrieved Passage: The intake of alcohol causes an initial surge in blood sugar, and later tends to cause levels to fall. Also, certain drugs can increase or decrease glucose levels...

Original Label: FP.
Model Prediction: no FP.

Comment: The comment says that straight alcohol does not affect blood sugar change, but the retrieved passage says otherwise.

Table 11: Inconsistencies between comment and retrieved passages by c-REALM from Wikipedia.

noticing that the presupposition is false (since in most cases, whether the presupposition is correct is not explicitly mentioned).

Secondly, there are 8% cases of labeling error in false positive cases. Note that for false positive cases, we did not distinguish between direct evidence and indirect evidence because there is no clear definition of “evidence” for non FP cases. For false negative cases, if there is a retrieved passage that can directly answer the question but the model fails in labeling, we consider this as a classification error rather than retrieving error, because the goal for retrieval is to retrieve passages that could give the answer to the question. The model also suffers more to classify given indirect evidence that requires reasoning, which matches our intuition.

Inherent disagreement and inconsistency issues contribute to the rest of the errors. We found that minor part (4%, 2% for false positive and false negative cases, respectively) of the error due to the inherent disagreements in labeling ambiguity. We also found that 2% of the false positive errors are due to whether the FP is critical to satisfy users information need based on the question. Furthermore, we also found that 14% of the errors are due to the comment and the retrieved passages are not inconsistent, causing label mismatch, however, they are not a labeling error because our ground truth annotator is not presented with additional passages when annotating. Example of these inconsistencies can be found in Table 11.

C.3 Discussion on inherent ambiguity and inconsistency on the web

Table 12 display examples for the category “Inherent disagreement: ambiguity”, “Inherent disagreement: criticalness”, and “Information on the web being inconsistent” from the human evaluation section of Section 5.2 and in Table 4.

9.1% of the errors is due to the inherent ambiguity of the criticalness of the FP, i.e., whether correcting the FP is critical to satisfy users’ information needed. For example, for the question “Why do things look darker when wet?” in Table 12, although our human rater found evidence on the internet that there exist things that look darker when dry, which would contradict the presupposition that (all) things look darker when wet, we believe that the question writer is mainly seeking an answer for the reason of the phenomenon that something looks darker when they are wet, and therefore, such FP is not critical to answer the users...
Inherent disagreement: Ambiguity

Q How are paintings or museum art classified as masterpieces? Some look like paint scratches and yet they are classics. Why is that?
C Great art isn’t just technical skill. Though a lot of those paintings that may look easy usually aren’t. But it’s also about having an original idea and expressing yourself in a way the world hasn’t seen before. (...)
comment Whether the question presupposes that a painting or an art is considered a masterpiece only depends on the technical skill exist in the question is debatable without the comment.

Q Why is Hydrogen so common on Earth and Helium quite rare?
C Hydrogen is highly reactive, it bonds to oxygen, forming water. Water is quite dense, even as a vapor, and is therefore quite durable in the atmosphere. Helium is a noble gas and nearly perfectly inert. Being unbound to any heavier elements, it quietly rises to the top of the atmosphere and is lost to space by various mechanisms. Hydrogen is lost over time, but only slowly.
comment There is an FP if the question is asking about hydrogen gas (see this webpage); however, if they are asking about hydrogen atom, there is no FP.

Inherent disagreement: Criticalness

Q Why do things look darker when wet?
C You know how when you vacuum the floor it makes those different colored lines? If you look closely the darker colored parts of the carpet are laying down and the lighter colored parts are standing up. Many things that are dry have little hairs or rough surfaces that are basically standing up like little mirrors to reflect light. When these get knocked over or filled with water they can’t reflect as well. A couple of damp riddles 1. What gets wetter as it dries 2. What gets darker as it dries

Information on the web being inconsistent

Q Why do 78% of Americans live paycheque to paycheck?
News on 06/07/2022: 58% Americans are living paycheck to paycheck.
News on 01/11/2019: 78% Americans are living paycheck to paycheck.

Q Why do pandas eat bamboo and when did they stop eating meat?
C Everyone so far has gone with the "pandas are so dumb" response so let me give you a proper answer. For a start, evolution is not an intelligent or forward thinking process. Bamboo may be low in energy, but it is abundant, grows quickly and not many other animals eat it. So for any animal that can evolve to consume it, there’s an open niche there to be taken. Now I’ll admit pandas aren’t the best creature at surviving, but they don’t really need to be. They live in an environment with abundant food and no predators or competitors, so all they need to do is sit around eating bamboo, expend minimal energy and produce just enough babies to keep the species going. Now that might not seem very efficient from a human perspective, but actually it’s a strategy that works surprisingly well, and pandas were doing absolutely fine until humans came along and started hunting them and destroying their habitat.

WWF: But they do branch out, with about 1% of their diet comprising other plants and even meat. While they are almost entirely vegetarian, pandas will sometimes hunt for pikas and other small rodents.
Science: Pandas are one of the world’s most fascinating vegetarians. Their digestive systems evolved to process meat, yet they eat nothing but bamboo—all day, every day. A new study reveals how these animals survive on a diet that should kill them.

Table 12: Inconsistencies and inherent ambiguity examples for human performance.

original question, and therefore the comment writer does not point it out.

Note that this is different than the “exception” examples mentioned in Table 2, as the comment explicitly pointed out the falsehood of the presupposition, and therefore we consider the FP as critical to answer the user’s information seeking need.

Furthermore, 22.7% of the errors in human performance is due to information on the web being inconsistent. For the question “why do 78% of Americans live paycheque to paycheck?”, News on 06/07/2022 points out that 58% Americans lives paycheck to paycheck, while News on 01/11/2019 pointed out that 78% of Americans live paycheck to paycheck. For the question “why do pandas eat bamboo and when did they stop eating meat?”, credible sources such as World Wide Fund(WWF) and Science says differently about whether panda eat meat or not.

34.1% of the errors are due to ambiguity, as analyzed in Section 3.3.

C.4 Details of the writing subtask

Example generations from each system are shown in Table 13, 14, and 15. As we discuss in Section 6.2, the unified model strongly prefers to generate the correction with prefix “It is not the case that”, or simply repeat or negate the presupposition, even though we do not restrict it to do so at inference time.

Details in Automatic Evaluation. We use sacreBLEU (Post, 2018) from the datasets library (Lhoest et al., 2021). We follow the preprocessing and evaluation script of unigram-F1 following Petroni et al. (2021), and the evaluation script of SentBERT following Reimers and Gurevych (2019).

Details in Human Evaluation. We conduct human evaluation for 200 questions on the test data. We recruit two student evaluators, who independently evaluate the presupposition and the correction given a question and its comment. They evalu-
**Question:** Why do prosecutors/courts seek/sentence prison time greater than the expected lifespan of the offender (i.e. 150 years in prison)? Why not simply sentence those criminals to 'life' in prison instead?

**Comment:** Sentencing options are written into state laws. Life in prison is different in state laws than 150 years. Some of it comes into play with the "cruel and unusual punishment" clause in the Constitution too. Life in prison may not be "cruel and unusual" for a murder sentence, but it might be for, say, child sex trafficking. But if you trafficked 10 kids and the sentence is 15 years for each one, you get an effective life sentence that will also stand up, Constitutionally, against a "cruel and unusual punishment" defense.

**Outputs human raters rate**

| Reference | Presupposition: | Correction: |
|-----------|----------------|-------------|
| It does not make sense to sentence a person to 150 years in prison if they can’t live that long anyways, prosecutors should use the life in prison sentence instead. |
| The defendant can argue the life in prison sentence as cruel and unusual, so the actual year sentence is better to give than the alternative. |

**GOLD-COMMENT track, Dedicated**

| Presupposition: | Correction: |
|----------------|-------------|
| Penalties should be able to be sentenced to life in prison. |
| Life in prison is different in state laws than 150 years in prison. |

**GOLD-COMMENT track, Unified**

| Presupposition: | Correction: |
|----------------|-------------|
| If a criminal is sentenced to life in prison, they should be sentenced to life in prison. |
| It is not the case that if a criminal is sentenced to life in prison, they should be sentenced to life in prison. |

**Main, Dedicated**

| Presupposition: | Correction: |
|----------------|-------------|
| Penalties should be able to be imposed on criminals for life. |
| The longer the sentence, the more likely the prosecution will seek to sentence the offender to life in prison. |

**Main, Unified**

| Presupposition: | Correction: |
|----------------|-------------|
| Prosecutor’s should seek prison time greater than the expected lifespan of the offender. |
| It is not the case that prosecutor’s should seek prison time greater than the expected lifespan of the offender. |

**Presupposition:** Scientists in the 1970s had a belief of an upcoming ice age.

**Correction:** The scientists of this time talked of global cooling in their near future, however they did not refer to this as an ice age.

**GOLD-COMMENT track, Dedicated**

| Presupposition: | Correction: |
|----------------|-------------|
| Scientists thought there would be a new ice age soon. |
| Scientists didn’t think that there would be a new ice age soon, they just thought that there would be one. |

**GOLD-COMMENT track, Unified**

| Presupposition: | Correction: |
|----------------|-------------|
| Scientists thought that there was going to be a new ice age soon. |
| Scientists didn’t think there was going to be a new ice age soon. |

**Main, Dedicated**

| Presupposition: | Correction: |
|----------------|-------------|
| Scientists in the 1970s thought that there was going to be a new ice age soon. |
| Scientists in the 1970s did not think that there was going to be a new ice age. |

**Main, Unified**

| Presupposition: | Correction: |
|----------------|-------------|
| Scientists in the 1970s thought that there was going to be a new ice age soon. |
| Scientists in the 1970s thought that there was going to be a new ice age. |

Table 14: Another example of the input and the output human raters are given for the human evaluation of the writing subtask. Note that human raters are not given which output is a reference or from which system.
Question: If the phases of the moon are due to the Earth’s shadow, why is the half moon a straight line/perfect semi circle, instead of a rounded shadow?

Comment: Unless you’re looking at a lunar eclipse, the part of the moon that’s not lit up is not in the Earth’s shadow, it’s in the moon’s shadow. The bright portion is facing the sun, and is therefore illuminated, and the dark portion is facing away from the sun, and therefore not illuminated.

Reference
Presupposition: If the phases of the moon are presumed to be the Earth’s shadow, then phases should never be a straight line due to the earth being rounded.
Correction: With the exception of the lunar eclipse, the phases of the moon are not caused by the shadow of the Earth.

GOLD-COMMENT track, Dedicated
Presupposition: The phases of the moon are due to the Earth’s shadow.
Correction: The part of the moon that is not lit up is in the moon’s shadow.

GOLD-COMMENT track, Unified
Presupposition: The phases of the moon are due to the Earth’s shadow.
Correction: It is not the case that the phases of the moon are due to the Earth’s shadow.

Main, Dedicated
Presupposition: Half moon is a straight line/perfect semi circle.
Correction: The moon is not a rounded shadow, it is a straight line.

Main, Unified
Presupposition: The phases of the moon are due to the Earth’s shadow.
Correction: It is not the case that the phases of the moon are due to the Earth’s shadow.

Table 15: Another example of the input and the output human raters are given for the human evaluation of the writing subtask. Note that human raters are not given which output is a reference or from which system.

In particular, each output is rated based on four aspects as follows.

Fluency measures the fluency of the generated text, mainly whether it have repetitions, spelling errors or grammatical errors, or gibberish.

0: Generated text have fluency errors.
3: Generated text is free of fluency errors.

Presupposition evaluates whether the generated presupposition is the valid one in the question and whether it is factually false according to the comment.

0: The presupposition is invalid, i.e., does not exist in the question.
1: The presupposition is valid, e.g., exists in the question, but it is not factually false.
3: The presupposition is valid and is factually false.

Correction evaluates whether the generated correction provides a valid correction to the presupposition based on the comment with no hallucinated information, and provides enough justification (rather than simply being a negated presupposition). The former considers correctness (precision of the information), while the latter considers adequacy (recall of the information)

0: The correction is wrong based on the comment, or the correction is hallucinated.
1: The correction is correct based on the comment, but no additional information is provided to justify, or is a simple negation of the presupposition.
2: The correction is correct based on the comment, but misses some details to fully justify the falsehood of presupposition.
3: The correction is correct and provide enough information to justify the falsehood of presupposition.

Consistency requires the generated assumption and correction should be on the same topic and negate each other.

0: The presupposition and correction are not about the same topic.
1: The presupposition and correction are on the same topic, but they are not negating each other, or the negation is not explicit.
3: The presupposition and correction are consistent: are on the same topic and negate each other.

The evaluators are paid 17 USD/hour. See Section 6.3 for the results and discussion.

D A case study with GPT-3
Large language models such as GPT-3 (Brown et al., 2020) have shown impressive performance
Q: If there’s an equal and opposite reaction for everything, how does any action happen? Isn’t it balanced out by the opposite reaction?

**FP:** The equal and opposite reaction apply to the same object.

**Corr:** Based on Newton’s Law of Motion, the equal and opposite reaction apply to different objects. Only forces that are applied to the same object would be cancelled out.

| GPT-3 given Q, temp=0.0: The equal and opposite reaction is not always instantaneous, so an action can still happen even if there is an equal and opposite reaction. |
|---|
| **comment** Factualy false. The equal and opposite reaction are always instantaneous. |

| GPT-3 given Q, temp=0.7: According to Newton’s third law of motion, “For every action, there is an equal and opposite reaction.” However, this only applies to objects interacting with other objects. In other words, if Object A exerts a force on Object B, then Object B will exert an equal and opposite force on Object A. However, if there is no other object for the force to be exerted on, then there is no equal and opposite reaction, and the force will simply cause the object to accelerate in the direction of the force. |
|---|
| **comment** Does not explicitly point out FP, and the correction of FP is factually wrong. |

| GPT-3 given Q, temp=0.7 (different sample): There is an equal and opposite reaction for every action, but this doesn’t mean that every action is balanced out by the opposite reaction. For example, if you push on a wall, the wall pushes back on you with an equal and opposite force. However, the wall doesn’t move because the force you’re exerting on it is balanced out by the force of the wall pushing back on you. |
|---|
| **comment** The correction of FP is factually wrong. In the scenario mentioned in the generation, the wall does not move because its mass is large. Besides, this scenario is not related to what the question is asking about. |

| GPT-3 given Q + “Or did I misunderstand anything?”, temp=0.7: No, you didn’t miss anything. The equal and opposite reactions do balance each other out, but the net result is still an action. This is because the reactions don’t happen instantaneously - there is a brief period of time during which one reaction is occurring without the other. During this time, the system is unbalanced and an action can occur. |
|---|
| **comment** Factualy false, and fail to identify FP. The equal and opposite reactions do not balance out, and they happen instantaneously. |

| GPT-3 given Q + “Or did I misunderstand anything?”, temp=0.7: Newton’s third law of motion states that for every action, there is an equal and opposite reaction. However, this does not mean that every action is perfectly balanced by an equal and opposite reaction. Instead, it means that the total force exerted by all objects on each other is always zero. |
|---|
| **comment** Does not explicitly point out FP, and provide adequate correction. |

| GPT-3 given Q + “Or do I have any misunderstanding?”, temp=0.7: There is an equal and opposite reaction for every action, but not every reaction is equal in magnitude to the action. For example, if you push on a wall, the wall pushes back on you with an equal and opposite force, but the force exerted by the wall is much less than the force you exerted. This is because the wall is much more massive than you are, so it takes more force to move it. |
|---|
| **comment** Factualy false. The force exerted by ‘you’ and the force exerted by the wall is equal. Besides, this is not what the question is asking about. It is answering a different question: why the wall won’t move given a force from you. |

Table 16: Response from InstructGPT given an example question. temp=0.0 is deterministic, and temp=0.7 is the default value in GPT-3. Generations are obtained by sampling multiple times or using slightly different templates. We did not cherry-pick these generations: we ran the model six times and report all.

| Q: How does flavored seltzer have 0 calories per serving but 10 calories per bottle? |
|---|
| **FP:** If something has 0 calories per serving then it cannot have any calories in total. |

| **Corr:** If a serving has under 5 calories, it can be rounded down to 0. |

| Instruct GPT-3: Flavored seltzer typically has 0 calories per serving, but 10 calories per bottle because the bottle contains multiple servings. |
|---|
| **comment** Does not point out that there can be > 0 calories per serving. |

| ChatGPT Mar 08th Snapshot: ... The reason that a bottle of flavored seltzer may list 10 calories on the label is because the servicing size is often one full bottle, which typically contains multiple servings. So, while a single serving may have 0 calories, the entire bottle may contain 10 calories or more.... |
|---|

| ChatGPT May 21th Snapshot: ... The discrepancy you mentioned regarding flavored seltzer’s calorie content per serving and per bottle is likely due to serving size and rounding conventions. When a flavored seltzer is labeled as having 0 calories per serving, it means that the amount of calories present in a single serving is so low that it falls below the threshold required for rounding up to the nearest whole calorie. This is typically 5 calories per serving. Consequently, the manufacturer can round down and label it as having 0 calories per serving... |
|---|

| **comment** Correct. |

Table 17: Response from Instruct GPT-3 and ChatGPT given an example question.

In generating a response to the question. We conduct small-scale evaluation of Instruct GPT-3, whose details are not public but is known as the best version of GPT-3. An example is depicted in Table 16. We find that most generations are roughly on the right topic,
e.g., all generations in Table 16 discuss Newton’s Law of Motion. However, they rarely correctly satisfy users information need:

- Most of them include information that is factually false, e.g., the equal and the opposite action are not instantaneous (1 4), their magnitude is not equal (2 6), or they do balance out (3).
- They are often not precisely about what the question is asking about. For instance, they discuss why an object may not move given a force, e.g., the wall does not move when you hit the wall (2 6). This is related to Newton’s Law of Motion, but not at all to the question.
- They do not explicitly identify false presuppositions. None of the generation mentions that the key misunderstanding is that the equal and opposite reaction apply to different objects, thus are not cancelled out. Sometimes the generation indicate some part of the question is wrong (indicates with ‘but’ or ‘However’) but does not precisely point out what is wrong, nor provide corrections.

It is possible performance could be improved with better prompting, but we leave this possibility to future work. We also experiment with ChatGPT in Mar 2023 and May 2023 in Table 17, but due to the closeness and the continuation of update, it is hard to evaluate and do an ablation study of the model, but we think the model is better than InstructGPT in generating answers that explicitly point out the false presupposition, but we leave the possibility to systematically evaluate this model on our task to future work.

E False Presuppositions in Other Data

While we focus on questions from an online forum due to the availability of large unlabeled data and the domain being fairly general, we argue that false presuppositions are not specific to such domains. In fact, false presuppositions are more prevalent when the domain is specific and requires expertise.

We analyze 50 random samples of unanswerable questions from QASPER (Dasigi et al., 2021), a dataset consisting of information-seeking questions on NLP research papers, posed by NLP experts. We find that, out of 48 questions that are unanswerable (2 of them turn out to have valid answers), 25% of them has false presuppositions, because the question writer does not have sufficient background knowledge or misses facts in the research paper.

Table 18 shows a subset of such questions, along with false presuppositions and their correction annotated by the author. Identification of false presuppositions requires external knowledge beyond the specific paper the question writer is reading (1), or requires understanding of details of the paper which may not be explicitly written with the exact same terms in the paper (2 and 3).

It should be noted that this percentage is a strict lower bound of true percentage and may be significantly underestimated since identification of false presupposition requires knowledge in NLP; the estimate will be higher when annotated by multiple NLP experts. Moreover, presuppositions will significantly more prevalent when question writers are non-expertise, unlike in QASPER whose question writers are NLP experts.

We did not annotate and experiment with QASPER because the data is relatively small (272 and 62 unanswerable questions on the training set and on the validation set, respectively), but future work can investigate this data as well we domain transfer of models.
Instructions (Click to collapse)

We will randomly select 1000 and test a very small number of workers in the main task (500) to achieve a satisfactory quality of 65%. To successfully complete your HIT, you must read the full instruction and examples in detail. Please expect about 1 hour doing HIT, but you will not get paid for it. After you complete the HIT, you will be paid $100.00.

Please make sure that your answers are correct in order to validate the task and maintain your qualifications.

In this task, you are given questions (as in the main task) and are told whether the question is subjective or objective. You will then answer the questions. You will go through the following steps for each question.

Step 1: Read the question, and if it is subjective or objective, answer.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (subjective)
Answer: No.

Example question: Are you happy today? (objective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Step 2: Decide if the question is subjective or objective.

1. Read the question and decide if it is subjective or objective.
2. If the question is subjective, provide an answer.
3. If the question is objective, provide an objective answer.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Step 3: Write down the assumption in the question that is wrong, as well as the correction made by the response. (Example: the concept is a simple negation of the question.)

Example question: Are you happy today? (subjective)
Answer: No.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Step 4: Follow the rules when writing for both subjective and objective questions.

1. Use the declarative sentence for both questions and corrections. Don't use the phrases with the question form that is used in the response. Your answer will not pass if you don't follow these rules.
2. Use the language from the question and the response as much as possible. If the question contains elements that are considered subjective or objective, use as much of that language as possible.
3. If the question is subjective, provide a subjective answer. If the question is objective, provide an objective answer.
4. If the question is subjective, provide an objective answer. If the question is objective, provide a subjective answer.
5. If the question is subjective, provide a subjective answer. If the question is objective, provide an objective answer.
6. If the question is subjective, provide a subjective answer. If the question is objective, provide an objective answer.
7. If the question is subjective, provide a subjective answer. If the question is objective, provide an objective answer.
8. If the question is subjective, provide a subjective answer. If the question is objective, provide an objective answer.

Example question: Are you happy today? (subjective)
Answer: No.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Example question: Are you happy today? (subjective)
Answer: Yes.

Example question: Are you happy tomorrow? (objective)
Answer: No.

Figure 2: The instruction we provided for our qualification task.
**Question 14:** Why do airplane flight tracks always make big arcs, rather than a "straight line" directly to your destination?

- Is this question subjective or nonsense?
  - [ ] Yes, the question is subjective or nonsense.  [ ] No, the question looks good.

**Response:** Because the earth is round and what you’re seeing is a projection on a 2D map of the shortest path on a sphere (the Earth).

- Is this response uninformative, bad quality or nonsense? (Do not assess whether the comment is factually correct.)
  - [ ] Yes, the response is uninformative, bad quality or nonsense.  [ ] No, the response looks good.

Does the response point out that any assumption made by the question writer is wrong? (Consider both explicit and implicit assumption. You should assume the response is always correct.)

- [ ] Yes, the comment points out that some assumptions made by the question writer is wrong.  [ ] No.

**What is that assumption in the question that is wrong?** (It should be a concise, declarative sentence, and use the language from the question as much as possible.)

- Airplane flight tracks are arcs.

**What is the correction to the response?** (It should be a concise, declarative sentence, and use the language from the question/comment as much as possible.)

- They appear to be arcs because the earth is round.

When you are done with writing, move on to the next question!

**Figure 3:** An example of our designed annotation interface.
The Responsible NLP Checklist used at ACL 2023 is adopted from NAACL 2022, with the addition of a question on AI writing assistance.
C2. Did you discuss the experimental setup, including hyperparameter search and best-found hyperparameter values?
   Appendix D.1

C3. Did you report descriptive statistics about your results (e.g., error bars around results, summary statistics from sets of experiments), and is it transparent whether you are reporting the max, mean, etc. or just a single run?
   Appendix D.1

C4. If you used existing packages (e.g., for preprocessing, for normalization, or for evaluation), did you report the implementation, model, and parameter settings used (e.g., NLTK, Spacy, ROUGE, etc.)?
   Section 4, Appendix D.4

D ✓ Did you use human annotators (e.g., crowdworkers) or research with human participants?
   Section 3, Appendix B

D1. Did you report the full text of instructions given to participants, including e.g., screenshots, disclaimers of any risks to participants or annotators, etc.?
   Appendix D.4, Figure 2, Figure 3

D2. Did you report information about how you recruited (e.g., crowdsourcing platform, students) and paid participants, and discuss if such payment is adequate given the participants’ demographic (e.g., country of residence)?
   Appendix B, Appendix D.4

D3. Did you discuss whether and how consent was obtained from people whose data you’re using/curating? For example, if you collected data via crowdsourcing, did your instructions to crowdworkers explain how the data would be used?
   We recruit people and people need to opt-in to participate in annotation. All our annotators were aware of the intent of the annotations.

D4. Was the data collection protocol approved (or determined exempt) by an ethics review board?
   Appendix B

D5. Did you report the basic demographic and geographic characteristics of the annotator population that is the source of the data?
   Appendix D.4