Unsupervised Commonsense Question Answering with Self-Talk

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Abstract

Natural language understanding involves reading between the lines with implicit background knowledge. Current systems either rely on pre-trained language models as the sole implicit source of world knowledge, or resort to external knowledge bases (KBs) to incorporate additional relevant knowledge. We propose an unsupervised framework based on self-talk as a novel alternative to multiple-choice commonsense tasks. Inspired by inquiry-based discovery learning (Bruner, 1961), our approach inquires language models with a number of information seeking questions such as “what is the definition of ...” to discover additional background knowledge. Empirical results demonstrate that the self-talk procedure substantially improves the performance of zero-shot language model baselines on four out of six commonsense benchmarks, and competes with models that obtain knowledge from external KBs. While our approach improves performance on several benchmarks, the self-talk induced knowledge even when leading to correct answers is not always seen as useful by human judges, raising interesting questions about the inner-workings of pre-trained language models for commonsense reasoning.

1 Introduction

Human level natural language understanding involves reading between the lines and relying on implicit background knowledge. Consider the scene in Figure 1: Alice let Bob stand in front of her at the concert. Using physical and social commonsense -- (i) Bob and Alice want to see the stage, and (ii) If Bob is taller, they would block Alice’s view -- one can infer that Alice is taller than Bob. Such examples are ubiquitous across natural language understanding (NLU) tasks such as reading comprehension (Hirschman et al., 1999) and recognizing textual entailment (Dagan et al., 2013), and even more so in tasks dedicated to commonsense reasoning such as the Winograd schema challenge (WSC; Levesque et al., 2012).

Most current NLU models rely on pre-trained language models (LMs; e.g. Radford et al., 2019; Devlin et al., 2019; Liu et al., 2019). The standard practice is to use task-specific data to fine-tune a pre-trained LM in a supervised manner. Alternatively, LM score is used to rank answer choices in a zero-shot setup (Wang et al., 2019; Sakaguchi et al., 2020). In both setups, pre-trained LMs yield improved performance upon prior methods, greatly due to the world knowledge that such LMs capture, having been trained on massive texts (Petroni et al., 2019; Davison et al., 2019).

Despite the performance boost, LMs as knowledge providers suffer from various shortcomings: (i) insufficient coverage: due to reporting bias, many trivial facts might not be captured by LMs (purple set in Figure 1), because they are rarely written about (Gordon and Van Durme, 2013). (ii) insufficient precision: the distributional training objective increases the probability of non-facts (light green set in Figure 1) that are semantically similar to true facts, as in negation (“birds cannot fly”; Kassner and Schütze, 2019). LMs excel in predicting the semantic category of a missing word, but might predict the wrong instance in that category (e.g., depending on the phrasing, BERT sometimes
Table 1: An example from each dataset used in this paper. The correct choice in each example is given in bold text.}

| Dataset          | Context + Question                                                                 | Choices                                                                 |
|------------------|-------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| COPA             | The man broke his toe.  
*What was the cause of this?*                                                            | 1) He got a hole in his sock.                                           |
|                  |                                                                                     | 2) He dropped a hammer on his foot.                                     |
| Common SenseQA   | *Where on a river can you hold a cup upright to catch water on a sunny day?*         | 1) *waterfall* 2) bridge 3) valley                                      |
|                  |                                                                                     | 4) pebble 5) mountain                                                  |
| MC-TACO          | [...] dream of becoming a judge. *How many years did it take for Mark to become a judge?* | 1) 63 years 2) 7 weeks                                                 |
|                  |                                                                                     | 3) 7 years 4) 7 seconds 5) 7 hours                                     |
| Social IQa       | In the school play, Robin played a hero in the struggle to the death with the angry villain.  
*How would others feel as a result?*                                                       | 1) sorry for the villain                                               |
|                  |                                                                                     | 2) hopeful that Robin will succeed                                     |
|                  |                                                                                     | 3) like Robin should lose the fight                                    |
| PIQA             | To separate egg whites from the yolk using a water bottle, you should                  | 1) [...] *Release, which creates suction and lifts the yolk.*             |
| WinoGrande       | Katrina had the financial means to afford a new car while Monica did not, since , had a high paying job. | 2) Monica                                                             |

predicts red as the color of a dove). Finally, (iii) it is unclear that LMs are capable of performing multiple reasoning steps involving implicit knowledge.

To increase the coverage of high-precision world knowledge and facilitate multi-hop reasoning by making intermediate reasoning steps explicit, prior work incorporated KBs (e.g. ConceptNet; Speer and Havasi, 2012) and knowledge-informed models into LM-based models (Xia et al., 2019; Bosset-lut and Choi, 2019; Chen et al., 2019).

In this paper, we study pre-trained LMs as an alternative to external KBs in providing knowledge to commonsense question answering tasks. We propose an unsupervised model that uses an LM as the answer scorer, and a (possibly different) LM as a knowledge source. We formulate the process of obtaining relevant knowledge as a self-talk, inquiry-based discovery learning (Bruner, 1961), with the following steps: 1) seeking out knowledge by generating natural-language “clarification questions” conditioned on a given context; 2) generating their corresponding answers (“clarifications”); and 3) incorporating the clarifications as additional context.

Our model does not rely on external knowledge or additional supervision. Yet, we show that on 4 out of 6 tasks it substantially improves upon a zero-shot baseline that relies on LM score alone and performs on par, and sometimes better than, models that use external knowledge sources.

Integrating external knowledge warrants discerning relevant and helpful facts for solving a particular instance. LMs further require identifying that a clarification is factually-correct. We show that even among the clarifications that helped the prediction, humans perceived many as unhelpful or even incorrect, demonstrating that LM-based models often solve problems correctly for seemingly incorrect reasons. Our results call for future research on robust and correct knowledge integration to LM-based question answering systems.

2 Tasks

We focused on the multiple-choice question answering tasks exemplified in Table 1 and detailed below. Each instance consists of an optional context, an optional question, and several answer choices. The development sets sizes vary from 100 (COPA) to 1,954 (Social IQa).

**COPA: Choice of Plausible Alternatives (Gordon et al., 2012):** Asking about either a plausible cause or a plausible result, among two alternatives, of a certain event expressed in a simple sentence.

**CommonSenseQA: commonsense Question Answering (Talmor et al., 2019).** General questions about concepts from ConceptNet. To increase the challenge, the distractors are related to the target concept either by a relationship in ConceptNet or as suggested by crowdsourcing workers.

**MC-TACO: Multiple Choice Temporal commonsense (Zhou et al., 2019).** Questions about temporal aspects of events such as ordering (Table 1), duration, stationarity, frequency, and typical time. The distractors were selected in an adversarial way using BERT.1

1To make this task compatible with the other tasks, we only kept a single correct answer per instance, making our results not comparable to previously reported results.
Social IQa: Social Interaction Question Answering (Sap et al., 2019b). Questions regarding social interactions, based on the ATOMIC dataset (Sap et al., 2019a). Contexts describe social interactions and questions refer to one of a few aspects (e.g. the subject’s motivation, following actions, etc.). The answers were crowdsourced.

PIQA: Physical Interaction Question Answering (Bisk et al., 2020). Questions regarding physical commonsense knowledge. Contexts are goals derived from an instruction website, typically involving less prototypical uses of everyday objects (e.g., using a bottle to separate eggs). The answers were crowdsourced, and an adversarial filtering algorithm was used to remove annotation artifacts.

WinoGrande (Sakaguchi et al., 2020). A large-scale version of WSC that exhibits less bias thanks to adversarial filtering and use of placeholders instead of pronouns. As opposed to WSC that was curated by experts, WinoGrande was crowdsourced with a carefully designed approach that produces diverse examples which are trivial for humans.

3 Models
A given instance consists of an optional context $c$, an optional question $q$, and answer choices: $a_i^{c=1}$. We first describe the baseline model, which makes the prediction based on the instance alone (Section 3.1). We then describe a knowledge-informed model that relies on external resources (Section 3.2). Finally, we discuss the proposed inquiry-based model, which uses a pre-trained LMs to produce clarifications (Section 3.3).

3.1 LM-only Baseline
We use a pre-trained language model $\text{LM}_{\text{a}}$ to score the plausibility of different text fragments. We experimented with the various LMs provided by the transformers package (Wolf et al., 2019): GPT (Radford et al., 2018), GPT2 (Radford et al., 2019, all sizes), a distilled GPT2 (Sanh et al., 2019), and XLNet (Yang et al., 2019, both sizes).

We assign each of the answer choices $a_i$ into the combination of the context and the question, and obtain $\text{opt}_i = \text{combine}(c, q, a_i)$. The combine function is computed differently for each task. For example, in COPA, where the question might be either about the cause or the effect of the context, we create the following texts for cause: “[context]. As a result, [choice]” and for effect: “[context]. The cause for it was that [choice]”.

We denote the score of each answer choice as $\text{score}(a_i) = \text{CE}(\text{opt}_i)$, where CE is cross-entropy loss defined as:

$$\text{CE}(t_1...t_n) = -\frac{1}{n} \sum_{i=1}^{n} \log_2 p_{\text{LM}_{\text{a}}}(t_i \mid t_1...t_{i-1})$$

We predict the $y = \arg\min_i \text{score}(a_i)$.

3.2 Baseline Model with External Knowledge
In the setup illustrated in Figure 2, each instance consists of an additional clarification list: $\text{CL} = \{cl_1,...,cl_m\}$. Those are text fragments containing potentially relevant knowledge for solving the instance. For instance, the clarification “The purpose of the internship is to help people find jobs” might help answering the question “which of Brett and Ian found a job less quickly after graduation?”. We don’t expect all the clarifications to be relevant and helpful for answering the main question. Instead, the model relies on the single clarification that increases its belief of a certain answer choice. Thus, the score of each answer choice is selected as the score of the text containing the clarification that most supports it, i.e., whose combination with it yields the minimal loss:

$$\text{score}(a_i) = \min_{cl \in \text{CL}} \text{CE}(\text{opt}_i + cl)$$

Again we predict $y = \arg\min_i \text{score}(a_i)$.
We extract clarifications from the following sources, exemplified in Figure 3.

**ConceptNet.** Similarly to previous work, we extract relation paths between words from the context and the question, and words from the answer choices. Since we incorporate the knowledge into the model as text, we convert each ConceptNet relation to a natural language template as in Davison et al. (2019). We limit the path length to 2 edges in order to maintain high precision.

**Corpus.** For pairs of words from the context and question and from the answer choices, we extract their joint occurrences (with minimum frequency of 100) in Google N-grams (Brants and Franz). This yields text fragments of up to 5 words rather than well-formed sentences, with the potential of describing the relationship between the two words (Shwartz and Dagan, 2018).

**COMET.** COMET (Bosselut et al., 2019) is a knowledge base construction model trained on the ATOMIC resource (Sap et al., 2019a) which consists of everyday situations along with multiple commonsense dimensions such as their causes, effects, pre- and post-conditions, etc. We generate all the dimensions unless we can generate specific relations that are more likely to help. Specifically, in Social IQa, we heuristically try to understand which type of relation in COMET the question asks for. In COPA, we use the pre-condition relations for cause questions (xIntent, xNeed) and the post-condition relations for effect questions (xEffect, xReact, xWant, oEffect, oReact, oWant). When possible, we replace personX with the syntactic subject of the context or the question.

### 3.3 Self-talk Model

Our proposed model makes the prediction identically to Figure 2, but extracts the clarifications from pre-trained LMs. We treat the knowledge extraction from LMs as a process of self-asking clarification questions about the context and “discovering” their answers. Figure 4 exemplifies this process for WinoGrande with a generator language model LMg. For the sake of simplicity, the illustration depicts the process of generating a single pair of clarification question and answer.

We start by generating multiple clarification questions conditioned on the context, by 1) concatenating one of several question prefixes, which we curated for each task (e.g. “What is the purpose of”, see the appendix); and 2) generating 5 questions for each prefix using Nucleus sampling with $p = 0.2$, i.e., sampling from the top 20% tokens (Holtzman et al., 2019). We limit the question length to up to 6 tokens excluding the prefix.

For each well-formed question that we obtained at the previous step, e.g. “What is the purpose of

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3This value was chosen in preliminary experiments and is significantly lower than the standard value for $p$ in the literature, which is typically around 0.9. We use a low value because we optimize for factual correctness, and our preliminary experiments have shown that lower $p$ values produce texts that are more “faithful” to their training corpus (at the price of being more bland).
**4 Results**

Table 2 displays the performance of the best model in each category according to the development accuracy. We report the performance of the following models: majority baseline, LM baseline (Baseline), LM-based model with external knowledge (Ext. Knowledge), Self-talk, supervised models from prior work when applicable (Pre. Sup), and human performance. Our zero-shot models are highlighted in purple.

As expected, the overall performance is worse for the zero-shot models compared to the state-of-the-art supervised models, but they perform substantially better than the majority baselines on most tasks, with the exception of WinoGrande where they only slightly outperform it. Among the LM-based models, self-talk performs on par or within a few points from the external knowledge model.

**Best LM.** Table 3 shows the ranking of the LMs according to their development accuracy averaged across the different knowledge sources. In general there is a preference to GPT-2, and in particular to the larger models, except for COPA in which the distilled version works best. A possible explanation might be that the language model distillation reduces the likelihood of rare words (Tang and Lin, 2020).
With respect to self-talk models, there is a rather MC-TACO which didn’t prove beneficial except for 40GB in GPT-2, both using web text). 5 Human Evaluation of the Clarifications than the sum of its parts. resources added noise, making the whole smaller accuracy, bringing it to 66.7). We assume that some clarifications from all the knowledge sources, differently LMs used as knowledge sources, with slight small difference in performance between the different LMs used as knowledge sources, with slight preference to GPT-2 in most datasets.

We also experimented with combining the clarifications from all the knowledge sources, which didn’t prove beneficial except for MC-TACO (where it added +7.9 points to the dev accuracy, bringing it to 66.7). We assume that some resources added noise, making the whole smaller than the sum of its parts.

## 5 Human Evaluation of the Clarifications

While the performance on the end task serves as an extrinsic evaluation for the quality of the generated clarifications, we are also interested in evaluating it intrinsically. From preliminary experiments we know that there is a high ratio of noisy clarifications. Thus, we analyze the clarifications that help predict the correct answer, i.e. clarifications with the best LM score in their instance and whose existence change the answer from an incorrect prediction by the baseline to a correct prediction by the model.

We sampled up to 50 such clarifications for each combination of task and knowledge source, using the best performing LM.3 We showed crowd-sourcing workers an instance along with a clarification question and its answer, and asked them: 1) whether the question is grammatical, not entirely grammatical but understandable, or completely not understandable; and if the answer was anything but understandable; and if the answer was anything but “completely not understandable”, 2) whether the question is relevant, i.e. on topic with the instance. We asked the same questions about the answer, in addition to: 3) whether the answer is factually correct or likely true; and 4) whether the answer adds helpful information to solve the instance.

The annotation task was carried out in Amazon Mechanical Turk. To ensure the quality of annotations, we required that the workers be located in the US, UK, or Canada, and have a 99% approval rate for at least 5,000 prior tasks. We aggregated annotations from 3 workers using majority vote. The annotations yielded moderate levels of agreement, with Fleiss Kappa \( \kappa = 0.43 \) (Landis and Koch, 1977). Among the different categories of annotations we measured pairwise accuracy, which ranged from 60.41% (the answer is factually correct) to 92.26% (the question is completely not understandable).

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3 We omitted COPA from the analysis due to its small size. See the appendix for examples.

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| Dataset  | Rank (Mean Dev Acc.) |
|----------|----------------------|
| COPA     | GPT2-L (60.6) > GPT2-T (58.6) > GPT2-XL (51.2) > Distil-GPT2 (48.8) > GPT2-M (40.4) > GPT2-XL (25.8) > GPT2-M (15.2) > GPT2-XL (15.2) > GPT2-M (10.0) > GPT2-L (10.0) |
| CSQA     | GPT2-L (58.6) > GPT2-XL (51.2) > GPT2-M (53.3) > GPT2 (58.6) > Distil-GPT2 (48.8) > GPT2-M (40.4) > GPT2-XL (25.8) > GPT2-M (15.2) > GPT2-L (10.0) |
| Social IQa| GPT2-L (51.2) > GPT2-XL (51.2) > GPT2-M (51.2) > GPT2-XL (37.1) > GPT2-M (40.4) > GPT2-L (26.1) > GPT2 (26.1) > GPT2-M (15.2) > GPT2-L (10.0) |
| PIQA     | GPT2-L (51.2) > GPT2-XL (51.2) > GPT2-M (51.2) > GPT2-XL (37.1) > GPT2-M (40.4) > GPT2-L (26.1) > GPT2 (26.1) > GPT2-M (15.2) > GPT2-L (10.0) |

Table 3: Ranking of LMs according to their dev accuracy averaged across knowledge sources for each dataset.

| Dataset  | Rank (Mean Dev Acc.) |
|----------|----------------------|
| COPA     | COMET (61.1) > GPT2-XL (58.6) > Google Ngrams (58.4) > GPT2-M (58.2) > XNLI-base (58.2) > GPT2 (58.1) > GPT2-XL (57.9) |
| CSQA     | COMET (51.2) > GPT2-L (51.2) > GPT2-XL (40.6) > GPT2-M (40.4) > XNLI-base (40.4) > GPT2-XL (33.1) |
| Social IQa| COMET (41.4) > GPT2-XL (40.9) > GPT2-L (40.6) > Distil-GPT2 (40.5) > XNLI-base (40.4) |
| PIQA     | Google Ngrams (60.5) > XNLI-base (60.2) > ConceptNet (60.2) > GPT2 (60.1) > GPT2-XL (60.1) > GPT2-M (60.0) |

Table 4: Ranking of knowledge sources according to their dev accuracy averaged across LMs for each dataset (for the sake of space, only the top 7 are listed).

WinoGrande, 2018), which works well for the simple sentences in COPA. The XLNet models perform poorly, perhaps due to their smaller training corpus (16GB vs 40GB in GPT-2, both using web text).

**Best Knowledge Source.** Among the knowledge informed models, COMET achieves the best performance across tasks. This likely happens first because COMET can dynamically generate predictions for any context, while the other two knowledge sources are static and lack coverage. Second, as expected, COMET improves the predictions for Social IQa, which was built based on the ATOMIC resource on which COMET is trained.

Table 4 sorts the knowledge sources based on the average development accuracy across LMs. PIQA and MC-TACO, tasks that require different types of knowledge from social commonsense, perform well with ConceptNet and Google Ngrams. With respect to self-talk models, there is a rather small difference in performance between the different LMs used as knowledge sources, with slight preference to GPT-2 in most datasets.

We also experimented with combining the clarifications from all the knowledge sources, which didn’t prove beneficial except for MC-TACO (where it added +7.9 points to the dev accuracy, bringing it to 66.7). We assume that some resources added noise, making the whole smaller than the sum of its parts.
Figure 6: Human evaluation of the clarifications, for each combination of task and knowledge source. **Top:** ratio of grammatical, not entirely grammatical but understandable, and completely not understandable clarifications. **Bottom:** percent of clarifications considered relevant, correct, and helpful. Answers in Social IQa were only evaluated for helpfulness when the clarification question was different from the main question (e.g. in ConceptNet).

For the sake of brevity, we focus on the analysis of the answers to the clarification questions. Figure 6 shows the human evaluation results for each combination of task and knowledge source. The top part of the figure shows that across tasks and resources, most clarifications are grammatical or at least understandable, with the exception of XLNet. The bottom part shows the percentage of clarifications considered relevant, correct, and helpful. Most clarifications were considered relevant to the context, around half of them were considered factually correct, and some 20-40% were considered helpful. Considering that these are all clarifications that indeed helped the model, this is an interesting though not completely unexpected finding: the model utilizes knowledge that humans wouldn’t consider as helpful, and likely also vice versa.

Breaking down by knowledge source, we observe that when the datasets were created using a knowledge source (ConceptNet for CommonSenseQA, and Social IQa uses ATOMIC, on which COMET is trained), clarifications from that resource are considered correct. We also note that somewhat surprisingly, relatively few ConceptNet clarifications were considered correct, despite limiting the relation paths up to 2 edges.

6 Related Work

6.1 External Knowledge in Neural Models

Approaches for incorporating external knowledge into a neural model consist of several components: (1) the task addressed; (2) neural model; (3) knowledge sources; and (4) incorporation method. Most models target tasks that require commonsense knowledge, such as the story cloze test (RockStories; Mostafazadeh et al., 2016) and machine comprehension tasks (Kočiský et al., 2018; Ostermann et al., 2018; Clark et al., 2018; Talmor et al., 2019). The neural component has recently shifted from biLSTM to transformer-based representations, specifically pre-trained LMs such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019).

With respect to the knowledge source, the vast majority of papers rely on ConceptNet to extract relation paths between concepts and entities identified in the input (Speer and Havasi, 2012, see an example in Figure 3). Additional resources include WordNet (Lin et al., 2017; Wang and Jiang, 2019), mining scripts from corpora (Lin et al., 2017), knowledge base embeddings (Chen et al., 2019; Xiong et al., 2019), hand-crafted rules (Lin et al., 2017; Tandon et al., 2018), and tools such as sentiment analyzers (Chen et al., 2019) and knowledge-informed LMs (Bosselut and Choi, 2019).

The external knowledge is typically incorporated into the neural model by learning a vector representation of the symbolic knowledge (e.g. subgraphs from ConceptNet), and attending to it via attention mechanism when representing the inputs (Bauer et al., 2018; Paul and Frank, 2019; Lin et al., 2019). Alternative approaches include using the knowledge to score answer candidates and prune implausible ones (Lin et al., 2017; Tandon et al., 2018), and training in a multi-task setup via auxiliary tasks.
pertaining to knowledge (Xia et al., 2019).

6.2 Extracting Knowledge from LMs

Pre-trained LMs such as GPT2 (Radford et al., 2019) and BERT (Devlin et al., 2019) capture various types of world knowledge. Petroni et al. (2019) showed that such LMs can be used in a KB completion task over ConceptNet and Wikidata (Vrandečić and Krötzsch, 2014) by converting KB relations into natural language templates and querying the LM for the missing part in the triplet (concept₁, relation, concept₂). For instance, querying BERT for suitable substitutes to the mask in “Dante was born in [MASK]” assigns the highest probability to Rome. Davison et al. (2019) similarly showed that BERT assigns higher scores to natural language fragments of true rather than fictitious ConceptNet triplets, and semi-automated the template creation by using GPT2 to score hand-crafted templates.

While both works have shown somewhat promising results, other work showed that knowledge extracted from LMs is expectancy not always accurate. Specifically, Kassner and Schütze (2019) showed that negated facts are also considered likely by the LM, while Logan et al. (2019) pointed out that LMs may over-generalize and produce incorrect facts such as “Barack Obama’s wife is Hillary”.

6.3 Generating Questions and Explanations

There are numerous research directions investigating automatic question generation (Vanderwende, 2008). Motivations vary from data augmentation to QA tasks (Du et al., 2017; Dhingra et al., 2018; Du and Cardie, 2018; Sachan and Xing, 2018) through conversational machine reading (Saefidi et al., 2018; Pan et al., 2019), simplifying questions to make them more easily answerable (Buck et al., 2018; Talmor and Berant, 2018; Perez et al., 2020), to using questions as means for other purposes such as sentence representation and summarization (Guo et al., 2018; Potash and Suleman, 2019).

In particular, our work is pertinent to previous work in producing clarifications questions and explanations. Rao and Daumé III (2019) worked on question from forums (e.g. Stack Exchange). They proposed a model that generates clarification questions and corresponding answers for a given question, using the question’s comments (clarification questions and answers) as supervision. Question-answer pairs were scored based on how much relevant information they add to the context.

Shen et al. (2019) developed an active learning framework for image captioning that learns to detect uncertainty about generated words and ask natural language questions to reduce its uncertainty. A visual question answering (VQA) model provides an answer which is then used to change the caption. The framework is trained with reinforcement learning, but the gold standard captions are used during a warmup steps and the VQA model is supervised.

Klein and Nabi (2019) proposed a joint question generation and question answering framework. They fine-tuned GPT2 on a question answering dataset to generate a question and an answer span for a given passage, and trained BERT to answer the generated question given the passage. Finally, Rajani et al. (2019) proposed a model for CommonSenseQA that generates explanations for its predictions. They collected human explanations and used them to fine-tune LMs to automatically generate explanations. These explanations were then added as additional inputs. The shortcoming of this approach is that it requires collecting specific human explanations for each new dataset.

7 Discussion and Conclusion

We presented an unsupervised framework for multiple choice commonsense tasks that generates and integrates background knowledge from pre-trained LMs. On most tasks, it performs substantially better than the baseline and similarly to a model that had access to external knowledge resources.

By design, our model makes a single additional reasoning step explicit. A preliminary experiment in which we incorporated clarification pairs to facilitate two hops got mixed results. An interesting future direction is to generate each clarification in response to the previous ones, in a dialogue setup (Saefidi et al., 2018). Another challenge is the “needle in a haystack” problem of the clarifications, and one way to address it is to develop a model that is capable of “introspection”, specifically knowing what it doesn’t know. A more structured knowledge generation might also make the combination of various knowledge sources more successful.

Filling in knowledge gaps and making implicit intermediate reasoning steps explicit is imperative going forward. We hope that our framework will facilitate future research in this area. Our code and data is available at github.com/vered1986/self_talk.
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| Dataset   | Question Prefix                                                                 | Answer Prefix                                      |
|-----------|--------------------------------------------------------------------------------|---------------------------------------------------|
| COPA      | What is the definition of                                                        | The definition of _ is                            |
|           | What is the main purpose of                                                       | The purpose of _ is to                             |
|           | What is the main function of a                                                    | The main function of a _ is                        |
|           | What are the properties of a                                                      | The properties of a _ are that                     |
| CommonSenseQA | What is a                                                                            | _ is                                             |
|           | What happened as a result of                                                       | As a result of _                                  |
|           | What might have caused                                                            | The cause of _ was                                |
| MC-TACO   | How long did this take?                                                            | This lasted for                                   |
|           | How often does this happen?                                                       | Every                                             |
|           | How many times did this happen?                                                   | This happened                                     |
|           | What happened first?                                                              | The first thing that happened was                 |
|           | What happened last?                                                               | The last thing that happened was                  |
| Social IQa | What will [NAME] want to do next?                                                 | [NAME] wanted                                     |
|           | What will [NAME] want to do after?                                                | [NAME] wanted                                     |
|           | How would [NAME] feel afterwards?                                                 | [NAME] felt                                       |
|           | How would [NAME] feel as a result?                                                | [NAME] felt                                       |
|           | How would you describe [NAME]?                                                    | [NAME] is a                                       |
|           | What kind of person is [NAME]?                                                    | [NAME] is a                                       |
|           | How would you describe [NAME] as a person?                                        | [NAME] is a                                       |
|           | Why did [NAME] do that?                                                           | [NAME] did this because they wanted               |
|           | Why did [NAME] do this?                                                           | [NAME] did this because they wanted               |
|           | What does [NAME] need to do beforehand?                                          | Before doing that, [NAME] first had to            |
|           | What does [NAME] need to do before?                                              | Before doing that, [NAME] first had to            |
|           | What does [NAME] need to do before this?                                         | Before doing that, [NAME] first had to            |
|           | What will happen to [NAME]?                                                       | [NAME]                                            |
|           | What will happen to [NAME] next?                                                  | [NAME]                                            |
|           | What will [NAME] do next?                                                         | [NAME]                                            |
|           | What did [NAME] do?                                                               | What [NAME] did was                               |
| PIQA      | How to                                                                            | The way to do _ is                               |
|           | How do you                                                                        | The way you do _ is                               |
|           | How can one                                                                       | One can _ by                                      |
|           | What can one do in order to                                                        | _ can be used for                                 |
|           | What should you use for                                                            | In order to _ one can                             |
|           | What is the definition of                                                          | For _ you should you use                          |
|           | What are the properties of a                                                      | The definition of _ is                            |
|           | What is _                                                                            | The properties of a _ are that                     |
|           | What does it mean to                                                               | _ means                                           |
| WinoGrande | What is the definition of                                                          | The definition of _ is                            |
|           | What is the main purpose of                                                         | The purpose of _ is to                             |
|           | What is the main function of a                                                     | The main function of a _ is                        |
|           | What are the properties of a                                                       | The properties of a _ are that                     |
|           | What is _                                                                            | _ is                                              |
|           | What does it mean to                                                               | _ means                                           |

Table 5: The question and answer prefixes used for each task. “_” in the answer prefix is replaced with the generated question (excluding the question mark), e.g. “What is the definition of a cat?” yields the following answer prefix: “The definition of a cat is”. The question and answer templates in Social IQa correspond to COMET dimensions. “[NAME]” is replaced with the syntactic subject of the sentence (see for example the first row in Table 6).
| Task | Context | Question | Clarification | Correct Answer | Source |
|------|---------|----------|---------------|---------------|--------|
| COPA | The player caught the ball. What was the cause for it? | Before doing that, what did Robin need to do before? | | Before healing, the players needed to go to the ball field. | Social Qa |
| COPA | The boy skipped dinner. He ate a big lunch. | What is the relationship between 'dinner' and 'lunch'? | The boy skipped dinner because they wanted to buy something good to eat. | Lunch is the opposite of dinner. | Social Qa |
| COPA | Working on the elaborate task was taxing. | What is the relationship between 'working' and 'concentration'? | | Concentration needs to happen. | Social Qa |
| COPA | What do professors primarily do? | What is the main function of a professor's teaching career? | | The main function of a professor's teaching career, is to teach students how they can improve their knowledge. | COPA |
| COPA | Growing up on a farm near St. Paul, L. Mark Bailey didn't dream of becoming a judge. | How many years did it take for Mark to become a judge? | | | COPA |
| COPA | Bailey saved money because they wanted to buy something. Bailey is seen as good with money. | How would you describe Bailey? | Bailey is seen as hardworking. | | Social Qa |
| COPA | Jan had been on vacation in Hawaii for a week. Last night, as a result, Jan wanted to return to her final destination. | What will Jan want to do next? | | As a result, Jan wants to get the dough out of the oven. | COPA |
| COPA | Robin proposed another solution after the first one was not successful. | What does Robin need to do before this? | Before doing that, Robin first had to do some research on how he could make it. | | COPA |
| COPA | Skylar always arrives 15 minutes early for class, takes extensive notes, and studies hard before tests. | How would you describe Skylar? | Skylar is a very good student who does well in the classroom. | | COPA |
| COPA | Carson was at a friend's house and they decided to play video games. | What does Carson need to do before this? | Before doing that, Carson first had to get his mother's permission before playing the game. | | COPA |
| COPA | Taylor is seen as someone who appreciates what Kendall does. | How would you describe Taylor? | Taylor is a good guy, but he's also an idiot. | | COPA |
| COMET | To cut circles out of dough without a cookie cutter. Use a glass by turning it upside down and using the rim. | What is the relationship between 'vacation' and 'work'? | Vacation is the opposite of work. | | COMET |
| PIQA | How can I slice up a banana? Use a knife, on a cutting board, and slice the banana into quarter sized slices. | What is the relationship between 'slice' and 'knife'? | Slice is a specific way of doing cut. Knife is used for cut. | | PIQA |
| PIQA | What pan to use for frying eggs? Nonstick pans are perfect for frying eggs. | What is the definition of a 'pan'? | A metal or ceramic vessel used in cooking. | | PIQA |
| PIQA | Sharpen a pencil. Use a knife. | What are the properties of a pencil? | The properties of a pencil are that it was already colorful will not break or be dulled. | | PIQA |
| COMET | Joel complained to Ian about the condition of the house. | What does Joel want as a result? | As a result, Joel wants to get rid of the clutter. | | Social Qa |
| WinoGrande | The hotel had a terrible gym but a nice restaurant; the something management attended to. | | | | COPA |
| GPT | Mark wanted to lose some weight by eating salad and drinking water. | What is the definition of 'workout routine'? | A workout routine is defined as any kind of exercise that involves doing physical activity. | | COPA |
| COPA | The parakeet flew to Hunter but flew past Samuel because Hunter had some bird seed in their hand. | What does it mean to be a 'bird'? | Be a 'bird' means the same thing as it does for us. | | COPA |
| COPA | Matt wanted to change either the plain bathroom or the colorful bedroom, but the | What is the definition of 'bedroom'? | A bedroom is defined as a room with a bed and nightstand in it. | | COPA |
| COPA | My employer offers a bonus of either a phone or a television, | What is the definition of 'phone'? | A phone is defined as device that connects a person directly into the world. | | COPA |

Table 6: Example instances from each dataset and the clarifications generated for them in various resources. We only include clarifications that helped the model predict the correct answer.