Generated Knowledge Prompting for Commonsense Reasoning

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Abstract

Despite their ability to capture large amount of knowledge during pretraining, large-scale language models often benefit from incorporating external knowledge bases, especially on commonsense reasoning tasks. This motivates us to explore how we can best leverage knowledge elicited from language models themselves. We propose generating knowledge statements directly from a language model with a generic prompt format, then selecting the knowledge which maximizes prediction probability. Despite its simplicity, this approach improves performance of both off-the-shelf and finetuned language models on four commonsense reasoning tasks, improving the state-of-the-art on numerical commonsense (NumerSense), general commonsense (CommonsenseQA 2.0), and scientific commonsense (QASC) benchmarks. Notably, we find that a model's predictions can improve when using its own generated knowledge, demonstrating the importance of symbolic knowledge representation in neural reasoning processes.

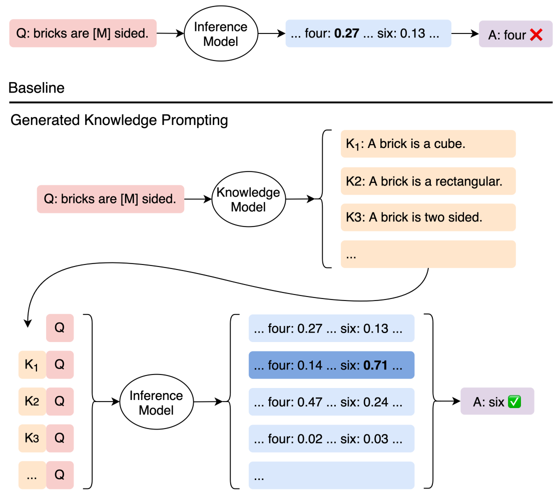

Figure 1: Top: Standard models select the highest probability prediction without reference to symbolic knowledge. Bottom: Generated knowledge prompting involves (i) generating question-specific symbolic knowledge, (ii) using the knowledge statement which best supports answering the question under the inference model.

1 Introduction

Performing commonsense reasoning requires commonsense knowledge. While pretrained language models implicitly contain a large amount of knowledge and can be directly used as inference models for commonsense reasoning (Trinh and Le, 2018; Yang et al., 2020), incorporating external knowledge bases can boost performance on some of these tasks (Mitra et al., 2019; Bian et al., 2021). On the other hand, language models themselves can serve the role as knowledge bases, as they allow for querying *symbolic knowledge* (i.e. knowledge expressed as natural language statements) (Petroni et al., 2019; Jiang et al., 2020). To leverage knowledge contained in language models for answering commonsense questions, most recent work manually designs dataset-specific, cloze-style templates to generate certain types of knowledge statements, such as clarifications (Shwartz et al., 2020) or contrastive explanations (Paranjape et al., 2021). However, tasks often require different types of knowledge that are beyond the scope of pre-defined templates (Table 1). How can we flexibly elicit useful knowledge of generic types from language models, and integrate the knowledge into prediction?

We develop a simple, yet effective, method for generating knowledge and using it to improve prediction performance. Our method uses two language models: a *knowledge model* which generates question-related knowledge statements using demonstrations formatted with a generic prompt, and an *inference model* which receives questions augmented with each knowledge statement, then uses the knowledge resulting in the highest probability for its prediction (Figure 1). This generic pro-

Dataset	Question / *Knowledge*	Prediction	Score
NumerSense	**the word children means [M] or more kids.** *The word child means one kid.*	one two	0.37 | 0.35 0.91
CSQA	**She was always helping at the senior center, it brought her what?** *People who help others are usually happier.*	feel better happiness	0.97 | 0.02 0.98
CSQA2	**Part of golf is trying to get a higher point total than others.** *The player with the lowest score wins.*	yes no	1.00 | 0.00 1.00
QASC	**Sponges eat primarily** *Sponges eat bacteria and other tiny organisms.*	cartilage krill and plankton	0.95 | 0.00 0.99

Table 1: Examples where prompting with generated knowledge rectifies the prediction. Each section shows correct answers in green, incorrect answers in red, and the prediction scores from the inference model that only receives the question (top) and the same model that receives a question augmented with the given model-generated knowledge (bottom).

cedure – which we refer to as *generated knowledge prompting* – improves performance of both off-the-shelf and finetuned models on numerical commonsense (NumerSense), general commonsense (CommonsenseQA 2.0), and scientific commonsense (QASC) benchmarks. Notably, it is effective when knowledge generation and inference are done with the same base language model.

We identify three factors that contribute to the performance of generated knowledge prompting (§3.4): (i) the *quality* of knowledge – e.g. knowledge from GPT-3 performs comparably to retrieval-based systems, (ii) the *quantity* of knowledge – i.e. performance improves with more knowledge statements, and (iii) the inference strategy for integrating knowledge. Our qualitative analysis (§3.5) suggests that generated knowledge can reduce commonsense question answering to explicit reasoning procedures – e.g. deduction – that are supported by off-the-shelf and finetuned language models. Our work provides a simple recipe for using language models as sources of symbolic knowledge in prediction tasks, and highlights the influence of symbolic knowledge in neural reasoning.

2 Generated Knowledge Prompting

We focus on multiple-choice tasks, which involve predicting an answer $a \in A_q$ given a question $q \in Q$, where the answer set A_q is finite and can vary by question, and both questions and answers are variable-length text sequences.

We introduce generated knowledge prompting as a two-step process. First, it uses a *knowledge model*, $p_G(k|q)$, to generate knowledge statements conditioned on the question:

$$K_q = \{k_m : k_m \sim p_G(k|q), m = 1 \dots M\},$$

where each knowledge statement k_m is a variable-length text sequence. Intuitively, each statement contains information that is relevant to the question (e.g. Table 1).

Second, generated knowledge prompting uses an *inference model*, $p_I(a|q, K_q)$, to predict an answer based on the question and knowledge statements,

$$\hat{a} = \arg\max_{a \in A_q} p_I(a|q, K_q)$$

It is a natural extension to using the inference model without knowledge (i.e. the *vanilla* setting), $\hat{a} = \arg\max_{a \in A_q} p_I(a|q)$.

Next, we describe how we use the knowledge model to generate high-quality, flexible knowledge, and how we integrate knowledge into the prediction of the inference model.

2.1 Knowledge Generation

We generate knowledge statements by prompting language models with demonstrations of useful question-related knowledge. The prompt uses the same generic format across all tasks. It consists of an instruction sentence, a few demonstrations of question-knowledge pairs, and ends with a question placeholder (Table 2).

For a given task, we gather five questions resembling those in the task, and write a corresponding knowledge statement for each question. Ideally, the knowledge statement provided should turn the commonsense problem into an explicit reasoning procedure. However, it should not be derived from simply plugging the answer into the question, so as to encourage more diverse generations. For example, for the question **Penguins have <mask> wings**, we can write the following knowledge statement: *Birds have two wings. Penguin is a kind of bird.*

Task	NumerSense	QASC
Prompt	Generate some numerical facts about objects. Examples: Input: **penguins have <mask> wings.** Knowledge: *Birds have two wings. Penguin is a kind of bird.* ... Input: **a typical human being has <mask> limbs.** Knowledge: *Human has two arms and two legs.* Input: **{question}** Knowledge:	Generate some knowledge about the input. Examples: Input: **What type of water formation is formed by clouds?** Knowledge: *Clouds are made of water vapor.* ... Input: **The process by which genes are passed is** Knowledge: *Genes are passed from parent to offspring.* Input: **{question}** Knowledge:

Table 2: Prompts for knowledge generation for two of our tasks, NumerSense and QASC. The prompt consists of an instruction sentence, five demonstrations of question-knowledge pairs, and ends with a question placeholder. For full prompts on all the tasks we evaluate on, see Appendix A.1.

The two sentences in the knowledge statement can be viewed as a complete set of premises for deductive reasoning. On the other hand, Penguins have two wings would be a poor knowledge statement to demonstrate, since it directly paraphrases the question and answer.

When generating knowledge for a particular question, we plug the question into the placeholder, and repeatedly sample generated continuations of this prompt to obtain a set of knowledge statements. The prompt is fixed when generating knowledge for questions from the same dataset. For full prompts on all the tasks we evaluate on, see Appendix A.1.

2.2 Knowledge Integration via Prompting

Suppose for each question q we generated M knowledge statements: $K_q = \{k_1, k_2, \dots, k_M\}$. We will *prompt* the inference model with the knowledge. First, the knowledge statements are individually prepended to the question, forming M knowledge-augmented questions:

$$q_0 = q, q_1 = [k_1||q], \dots, q_M = [k_M||q]$$

where $[\cdot||\cdot]$ denotes text concatenation. For each choice a, we define an aggregated score using the augmented question that best supports it under the inference model:

$$p_I(a|q, K_q) \propto \max_{0 \le m \le M} p_I(a|q_m). \quad (1)$$

Intuitively, this method favors knowledge that strongly supports one of the choices, while filtering out knowledge that fails to let the inference model make a resolute decision. The predicted answer is then,

$$\hat{a} = \arg\max_{a \in A_q} \max_{0 \le m \le M} p_I(a|q_m),$$

which is the choice that gets most support from one of the knowledge statements. This prediction is grounded in a single knowledge statement, which we refer to as the *selected knowledge*:

$$\hat{k} = k_{\hat{m}} \text{ where } \hat{m} = \arg\max_{0 \le m \le M} \max_{a \in A_q} p_I(a|q_m).$$

3 Experiments

3.1 Datasets and Task Setup

We evaluate generated knowledge prompting on four commonsense reasoning datasets: NumerSense (NS), CommonsenseQA (CSQA), CommonsenseQA 2.0 (CSQA2), and QASC. These datasets encompass a diversity of reasoning and problem formats.

For knowledge generation, we use GPT-3 (Brown et al., 2020), where our few-shot prompting method is most effective. Generally, we generate $M = 20$ knowledge statements for each question with nucleus sampling $p = 0.5$ (Holtzman et al., 2019), and discard repetitions and empty strings. Generation is terminated when it exceeds 64 tokens or hits the \n token. An exception is CSQA2, where we choose $M = 5$ and allow for up to 128 tokens in each generation.

For inference, we use off-the-shelf T5 (Raffel et al., 2019) and GPT-3 models, as well as finetuned models that are state-of-the-art on each dataset: for CSQA and QASC we use UnifiedQA (UQA) (Khashabi et al., 2020), and for CSQA2 we use Unicorn (Lourie et al., 2021).

NumerSense (Lin et al., 2020) consists of numerical statements about common objects and concepts where for each sentence we need to recover a masked number word. The options are integers ranging from zero to ten, plus the word *no*, so the task can be framed as a multiple-choice problem. For zero-shot T5 inference (which is the state-of-the-art), we follow Zhang (2021) which uses a text-infilling setup and chooses the option with highest likelihood on its token(s). We also implement zero-shot GPT-3 inference, where we plug in each option to the sentence and compute the answer probability as the generative probability of the entire sentence:

$$p_I(a|q) = p_{\text{GPT3}}(q.\text{replace}(\text{<mask>}, a))$$

CSQA (Talmor et al., 2019) is a 5-way multiple-choice QA dataset about common world scenarios. For zero-shot T5 inference, we format the question as text-infilling, and predict the choice with highest sequence-to-sequence language modeling probability. For inference with finetuned T5 (including the state-of-the-art UnifiedQA), we use the same multiple-choice text format as in Khashabi et al. (2020).

CSQA2 (Talmor et al., 2021) is a binary classification dataset where we need to judge whether commonsense statements are true or false. For inference, we use the state-of-the-art Unicorn (Lourie et al., 2021) finetuned on CSQA2. The question is formatted consistently with Talmor et al. (2021).

QASC (Khot et al., 2020) is an 8-way multiple-choice QA dataset about grade school science. This dataset additionally includes two pieces of background knowledge per question, whose composition fully answers the question. We implement inference with zero-shot T5 and finetuned T5 (including the state-of-the-art UnifiedQA), using the same format as in CSQA, respectively.

3.2 Baselines

We consider the following alternative knowledge generation methods as baselines:

No knowledge (∅). We refer to inference without any knowledge integration as the *vanilla* baseline.

Random sentences (R). Sampling random sentences from the language model without conditioning on the question.

Context sentences (C). Sampling sentences from the context of the question. This is implemented by sampling text continuations of the question from an autoregressive language model.

Gold knowledge (G). For each QASC question, the dataset contains gold knowledge: a *combined* fact sentence which directly answers the question, and two *separate* fact sentences which, when taking their composition, derive the combined fact sentence. We experiment with using either (1) the *gold combined fact* ($G1$), or (2) the *gold separate facts* ($G2$).

	Inference	Knowledge	dev	test
NS	T5-11b	ours	**78.0**	**79.24 | 72.47**
	Prev. SOTA (no IR)*		–	72.61 | 66.18
	IR SOTA**		–	70.41 | 65.10
CSQA	UQA-11b-ft	ours	85.34	–
	Prev. SOTA#		–	79.1
CSQA2	Unicorn-ft	ours	**72.37**	**73.03**
	Prev. SOTA (no IR)†		69.9	70.2
	IR SOTA††		74.0	73.3
QASC	UQA-11b-ft	ours	**84.02**	**80.33**
	Prev. SOTA (no IR)‡		81.75	76.74
	IR SOTA‡‡		–	89.57

Table 3: Comparison with state-of-the-art. For NumerSense (**NS**), the test set result consists of two splits: test-core and test-all. *: T5-11b 1.1 +digits (Submission by ISI Waltham). **: T5-11b + IR (Yan, 2021). #: UQA-11b-ft (Khashabi et al., 2020) (SOTA of single-model methods without referencing ConceptNet). †: Unicorn-ft (Talmor et al., 2021). ††: Unicorn-ft + Google snippets (Talmor et al., 2021). ‡: UQA-11b-ft (Khashabi et al., 2020). ‡‡: UQA-11b-ft + IR (Khashabi et al., 2020).

For the random sentences and context sentences methods, we sample the same number of statements per question as in our knowledge generation method (i.e. $M = 20$). We use GPT2-large (Radford et al., 2019) as the generator with nucleus sampling $p = 0.9$ and temperature $\tau = 0.5$; generation is terminated when hitting a period token. For gold knowledge, it is implied that $M = 1$ or 2.

3.3 Overall performance.

New state-of-the-art. Table 3 compares our method with the previous state-of-the-art. In each case we apply our method on top of the same inference model used in the previous SOTA. On NumerSense, we achieve a 6% improvement over the previous best method based on the zero-shot T5 model. The previous SOTA among non-IR methods on CSQA2 is based on the finetuned Unicorn model, upon which we improve by 2%. For QASC, the previous SOTA is based on the finetuned UnifiedQA model, which we improve by 3%.

Zero-shot settings. Our method shows the greatest improvement on off-the-shelf inference models. As shown in Table 4, our method improves zero-shot inference models by 7% to 10% across NumerSense, CSQA, and QASC. We do not evaluate this on CSQA2 due to the poor calibration of zero-shot models on this dataset.

	Inference	Knowledge	dev	test
NS	T5-11b	–*	67.5	70.23 | 64.08
		ours	**78.0**	**79.24 | 72.47**
	GPT-3	–	72.0	74.91 | 66.34
		ours	**81.0**	**80.74 | 73.46**
CSQA	T5-11b	–	39.89	–
		ours	**47.26**	–
QASC	T5-11b	–	48.16	44.89
		ours	**58.32**	**55.00**

Table 4: Improvement on zero-shot models. *: T5-11b baseline on NumerSense (Zhang, 2021).

	Inference	Knowledge	dev	test
CSQA	UQA-11b	–	76.99	–
		ours	**78.71**	–
	T5-11b-ft	–	83.54	–
		ours	**83.78**	–
	UQA-11b-ft	–	85.18	–
		ours	**85.34**	–
CSQA2	Unicorn-ft	–†	69.9	70.2
		ours	**72.37**	**73.03**
QASC	UQA-11b	–	67.93	67.07
		ours	**74.41**	**75.33**
	T5-11b-ft	–	76.03	73.91
		ours	**78.62**	**77.17**
	UQA-11b-ft	–	81.75	76.74
		ours	**84.02**	**80.33**

Table 5: Improvement on finetuned models. **-ft**: model finetuned on the corresponding dataset. †: Unicorn-ft baseline of CSQA2 (Talmor et al., 2021).

Supervised settings. Table 5 indicates that our method consistently improves upon the vanilla baseline set by finetuned inference models (though for smaller magnitude than on off-the-shelf inference models). The improvement can be as large as 8% (UQA-11b on QASC). Meanwhile, we note that the gains tend to become smaller when the inference model is directly finetuned on in-domain data (i.e. models with suffix **-ft**).

3.4 Quantitative Analysis

Our method is comparable with retrieval-based knowledge prompting. One of the top NumerSense submissions retrieves sentences from Wikipedia and GenericsKB, the latter of which is also used to build the NumerSense training set, and prepends these texts to the question. Such retrieved knowledge only improved inference accuracy by 0.18% on test-core and 1.02% on test-all, while our method further outperforms it by 8.83% and 7.37%, respectively (Table 3). This indicates that knowledge elicited from models can be more helpful for inference than that retrieved from a loosely related knowledge base. We also compare our generated knowledge with Google-retrieved knowledge on the CSQA2 task. Although we are not able to beat the web knowledge at inference, our method still bridges the knowledge gap without referring to Google search.

	Knowledge Generation	QASC-dev
$\varnothing$	vanilla baseline	48.16
R	Random sentences	48.70
C	Context sentences	51.30
K	ours	**58.32**
$G2$	Gold separate facts	76.89
$G1$	Gold combined facts	88.55

Table 6: Performance with different knowledge generation methods. Measured on QASC dev set with T5-11b inference model.

Our method outperforms template-based knowledge generation. Self-talk (Shwartz et al., 2020) uses manually-designed templates to elicit knowledge statements from language models. We compare our method with self-talk on the CSQA task. For fair comparison, we use GPT-3 as the knowledge generator in self-talk, and bound the number of generations to $M = 20$ per question. Other hyperparameters and templates are kept the same as their original paper. Using the T5-11b inference model, self-talk gets 45.37% accuracy on the CSQA dev set, which is 1.89% below our method; using the UQA-11b inference model, self-talk achieves 77.97%, which is 0.73% below ours. Our method makes larger improvements over the baseline than self-talk, showing that it is better at eliciting relevant knowledge from models.

Analysis on the quality of knowledge. We compare the quality of knowledge from different knowledge generation methods in terms of their effectiveness when used to prompt the inference model. Table 6 shows the performance with respect to each knowledge generation method. Random sentences barely help the inference model, whereas context sentences of the question provide some improvement. Knowledge generated by our method shows a much more significant improvement, which implies that our knowledge is of higher quality. Nevertheless, prompting and integrating the gold knowledge can provide far more improvement to the infer-

Knowledge Quantity (M)	QASC-dev
0	48.16
1	56.05
2	56.59
5	57.67
10	57.78
20	**58.32**

Table 7: Performance with different number of generated knowledge statements per question. Measured on QASC dev set with the GPT-3 knowledge model and T5-11b inference model.

Integration algo	QASC-dev
ours	**58.32**
Mixture-of-Experts	56.26
Product-of-Experts	55.94

Table 8: Performance with different knowledge integration algorithms. Measured on QASC dev set with the GPT-3 knowledge model and T5-11b inference model.

ence model, indicating that progress can be made by generating even better knowledge.

Better performance with more knowledge. We analyze the impact of the number of knowledge statements to generate, M, and show the results in Table 7. The accuracy measured on the QASC dev set increases consistently with the quantity of knowledge statements.

Analysis on the integration algorithm. In addition to the knowledge integration method described in §2.2, we experiment with two alternatives: Mixture-of-Experts (MoE) and Product-of-Experts (PoE). These make the following modifications to Equation 1, respectively:

$$\text{MoE: } P_I(a|q, K_q) \propto \sum_{0 \le m \le M} p_I(a|q_m), \quad (2)$$

$$\text{PoE: } P_I(a|q, K_q) \propto \prod_{0 \le m \le M} p_I(a|q_m). \quad (3)$$

The results in Table 8 indicate that our method – i.e. adaptively choosing the best knowledge to rely on – is best among the three.

Lightweight models and amplification. The size of inference models affects the magnitude of improvement. Table 9 shows the NumerSense performance gains under different sizes of inference models. As we use smaller inference models, the performance improvement increases drastically. In particular, with our method the smallest T5 model

NumerSense-dev			
Inference	**Baseline**	**+Knowledge**	**Δ**
GPT-3 (175B)	72.0	81.0	+9.0
T5-11b (11B)	67.5	78.0	+10.5
T5-3b (2.8B)	55.5	75.0	+19.5
T5-large (770M)	43.5	73.5	+30.0
T5-base (220M)	33.0	63.0	+30.0
T5-small (60M)	23.0	55.0	+32.0

Table 9: Improvement on different sizes of inference models. Measured on Numersense dev set with the GPT-3 knowledge model.

is as powerful as the T5-3b baseline, and T5-large outperforms the GPT-3 baseline. This indicates that symbolic knowledge can enable high performing, yet lightweight, inference models. Furthermore, the improvement does not diminish as inference model becomes as big as the knowledge generation model, and the inference by GPT-3 can benefit by 9.0% from the knowledge elicited from itself. This indicates that our method can somewhat *amplify* the useful knowledge already possessed by the model, making inference more powerful.

3.5 Qualitative Analysis

Table 10 shows a few examples where the generated knowledge rectifies the prediction. Due to space constraints we only show the *selected knowledge* (§2.2) for each question. In all examples, the vanilla inference process assigns a higher score for the distractor than the correct answer, while with knowledge prompting, the correct answer is assigned a much higher score and beats the distractor. Prompting with generated knowledge can transform commonsense reasoning into explicit reasoning procedures such as paraphrasing, induction, deduction, analogy, abductive reasoning, logical elimination, negation, and numerical reasoning.

4 Related Work

Knowledge can be elicited from pretrained language models. Numerous works have shown that pretrained language models implicitly contain large a amount of knowledge that can be queried via conditional generation (Davison et al., 2019; Petroni et al., 2019; Jiang et al., 2020). Consequently, these models can directly perform inference on tasks like commonsense reasoning (Trinh and Le, 2018; Yang et al., 2020), text classification (Shin et al., 2020; Puri and Catanzaro, 2019), and natural language inference (Shin et al., 2020; Schick and Schütze,

Dataset	Question / *Knowledge*	Prediction	Score	Reasoning
NumerSense	**clams have evolved to have [M] shells.**	no	0.37 | 0.18	Commonsense
	Clams have a bivalve shell.	two	0.89	Paraphrasing
NumerSense	**an easel can have [M] or four legs.**	two	0.45 | 0.45	Commonsense
	A tripod is a kind of easel.	three	0.46	Induction
CSQA	**Where does a heifer's master live?**	slaughter house	0.89 | 0.01	Commonsense
	The master of a heifer is a farmer.	farm house	0.92	Deduction
CSQA	**Aside from water and nourishment what does your dog need?**	walked	0.55 | 0.04	Commonsense
	Dogs need attention and affection.	lots of attention	0.91	Elimination
CSQA	**I did not need a servant. I was not a what?**	in charge	0.47 | 0.32	Commonsense
	People who have servants are rich.	rich person	0.99	Abduction
CSQA2	**Part of golf is trying to get a higher point total than others.**	yes	1.00 | 0.00	Commonsense
	The player with the lowest score wins.	no	1.00	Negation
CSQA2	**Eighth plus eight is smaller than fifteen.**	yes	0.97 | 0.03	Commonsense
	Eighth plus eight is sixteen, which is larger than fifteen.	no	1.00	Numerical
QASC	**[M] is used for transportation.**	plastic	0.41 | 0.12	Commonsense
	Bicycles are used for transportation.	boats	0.74	Analogy

Table 10: Examples where prompting with generated knowledge reduces the reasoning type and rectifies the prediction. The first row of each section is the original question and the inference results associated with it; the second row is a model-generated knowledge sentence that prompts the inference model. We show correct answers in green, distractors in red, and their corresponding scores assigned by the inference model.

2021). Inspired by these observations, we elicit question-related knowledge in a symbolic, explicit form from the language models and use them to guide the inference.

Leveraging external knowledge for commonsense reasoning. Several works use external commonsense knowledge bases to make improvements on various NLP tasks, including commonsense reasoning. One approach is injecting commonsense knowledge into language models, either by pretraining on knowledge bases (Ma et al., 2021; Chang et al., 2020; Mitra et al., 2019; Zhong et al., 2019) or finetuning the model so that it can reason with additional knowledge retrieved from the knowledge bases (Chang et al., 2020; Mitra et al., 2019; Bian et al., 2021). Another direction is grounding the question into a knowledge graph and running inference with graph-based reasoning (Lin et al., 2019; Lv et al., 2020; Yasunaga et al., 2021).

A common prerequisite of these methods is a high-quality, high-coverage, in-domain commonsense knowledge base (Ma et al., 2019). Some commonsense reasoning datasets are derived from existing knowledge bases; for example, CommonsenseQA (Talmor et al., 2019) is derived from ConceptNet (Speer et al., 2017), Social IQA (Sap et al., 2019b) is derived from ATOMIC (Sap et al., 2019a), and αNLI (Bhagavatula et al., 2019) is derived from ROC-Stories (Mostafazadeh et al., 2016). For such datasets, it is natural to elicit related knowledge from the underlying knowledge base that derived them, and typically this would demonstrate considerable gains (Mitra et al., 2019; Chang et al., 2020). However, if there is a domain mismatch between the dataset and the knowledge base, such gains tend to diminish (Mitra et al., 2019; Ma et al., 2019). This becomes a bottleneck when encountering datasets that have no suitable knowledge base (e.g. NumerSense (Lin et al., 2020) and CommonsenseQA 2.0 (Talmor et al., 2021)), or when the system needs to handle commonsense queries that do not fit in any of the commonsense domains represented by an existing knowledge base. Our work overcomes this difficulty by leveraging pretrained language models as the source of commonsense knowledge.

Augmenting questions with generated text. Recently, several works show that model performance on commonsense reasoning can be boosted by augmenting the question with model-generated text, such as clarifications, explanations, and implications. Self-talk (Shwartz et al., 2020) elicits clarifications to concepts in the question and appends them to the inference model input. Contrastive

Explanations (Paranjape et al., 2021) prompts inference models with generated explanations that contrast between two answer choices. The aforementioned methods depend on task-specific templates to inquire the generator, which means they are only capable of eliciting a limited variety of knowledge and require hand-crafting to transfer to new tasks. Other explanation-based methods (Latcinnik and Berant, 2020; Rajani et al., 2019) finetune the generator model so that it produces explanations that are used for question augmentation. DynaGen (Bosselut et al., 2021) uses pretrained commonsense models to generate implications of a question and expands the inference input with these generations. However, its usage of COMeT (Bosselut et al., 2019) as the generator confines its applicability to the social commonsense domain. Our method contributes to this general line of research, yet different from these previous methods that often make *a priori* assumptions on the type of knowledge to generate, we approach this from a reasoning perspective and aim to generate arbitrary knowledge that can support an explicit reasoning procedure, making our method flexible, easy-to-transfer, and engineering-efficient.

5 Conclusion

We propose generated knowledge prompting, a simple method to elicit and integrate knowledge from pretrained language models so as to improve performance on commonsense reasoning tasks. Our method offers a generic approach for incorporating symbolic knowledge into off-the-shelf and finetuned language models. It is effective across multiple datasets, sets the new state-of-the-art on three commonsense reasoning tasks, and works under a variety of settings.

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A Appendix

A.1 Prompts for Knowledge Generation

Table 11 through 14 shows the full prompts for knowledge generation that we use for each evaluated task: NumerSense, CSQA, CSQA2, and QASC.

Task	**Prompt**
NumerSense	Generate some numerical facts about objects. Examples: Input: **penguins have <mask> wings.** Knowledge: *Birds have two wings. Penguin is a kind of bird.* Input: **a parallelogram has <mask> sides.** Knowledge: *A rectangular is a parallelogram. A square is a parallelogram.* Input: **there are <mask> feet in a yard.** Knowledge: *A yard is three feet.* Input: **water can exist in <mask> states.** Knowledge: *There states for matter are solid, liquid, and gas.* Input: **a typical human being has <mask> limbs.** Knowledge: *Human has two arms and two legs.* Input: **{question}** Knowledge:

Table 11: Prompt for knowledge generation on NumerSense. Demonstration examples are manually written and the knowledge enables explicit reasoning procedures to answer the input question.

Task	**Prompt**
CSQA	Generate some knowledge about the concepts in the input. Examples: Input: **Google Maps and other highway and street GPS services have replaced what?** Knowledge: *Electronic maps are the modern version of paper atlas.* Input: **The fox walked from the city into the forest, what was it looking for?** Knowledge: *Natural habitats are usually away from cities.* Input: **You can share files with someone if you have a connection to a what?** Knowledge: *Files can be shared over the Internet.* Input: **Too many people want exotic snakes. The demand is driving what to carry them?** Knowledge: *Some people raise snakes as pets.* Input: **The body guard was good at his duties, he made the person who hired him what?** Knowledge: *The job of body guards is to ensure the safety and security of the employer.* Input: **{question}** Knowledge:

Table 12: Prompt for knowledge generation on CSQA. Demonstration examples are selected from the CSQA training set; we manually write relevant knowledge for each input question.

Task	Prompt
CSQA2	Generate some knowledge about the input. Examples: Input: **Greece is larger than mexico.** Knowledge: *Greece is approximately 131,957 sq km, while Mexico is approximately 1,964,375 sq km, making Mexico 1,389% larger than Greece.* Input: **Glasses always fog up.** Knowledge: *Condensation occurs on eyeglass lenses when water vapor from your sweat, breath, and ambient humidity lands on a cold surface, cools, and then changes into tiny drops of liquid, forming a film that you see as fog. Your lenses will be relatively cool compared to your breath, especially when the outside air is cold.* Input: **A fish is capable of thinking.** Knowledge: *Fish are more intelligent than they appear. In many areas, such as memory, their cognitive powers match or exceed those of 'higher' vertebrates including non-human primates. Fish's long-term memories help them keep track of complex social relationships.* Input: **A common effect of smoking lots of cigarettes in one's lifetime is a higher than normal chance of getting lung cancer.** Knowledge: *Those who consistently averaged less than one cigarette per day over their lifetime had nine times the risk of dying from lung cancer than never smokers. Among people who smoked between one and 10 cigarettes per day, the risk of dying from lung cancer was nearly 12 times higher than that of never smokers.* Input: **A rock is the same size as a pebble.** Knowledge: *A pebble is a clast of rock with a particle size of 4 to 64 millimetres based on the Udden-Wentworth scale of sedimentology. Pebbles are generally considered larger than granules (2 to 4 millimetres diameter) and smaller than cobbles (64 to 256 millimetres diameter).* Input: **{question}** Knowledge:

Table 13: Prompt for knowledge generation on CSQA2. Demonstration examples are selected from the CSQA2 training set; we use the annotated *Google Featured Snippet* as the knowledge.

Task	Prompt
QASC	Generate some knowledge about the input. Examples: Input: **What type of water formation is formed by clouds?** Knowledge: *Clouds are made of water vapor.* Input: **What can prevent food spoilage?** Knowledge: *Dehydrating food is used for preserving food.* Input: **The process by which genes are passed is** Knowledge: *Genes are passed from parent to offspring.* Input: **The stomach does what in the body?** Knowledge: *The stomach is part of the digestive system.* Input: **What can cause rocks to break down?** Knowledge: *Mechanical weathering is when rocks are broken down by mechanical means.* Input: **{question}** Knowledge:

Table 14: Prompt for knowledge generation on QASC. Demonstration examples are selected from the QASC training set; we use one of the gold separate facts as the knowledge.