ArT: All-round Thinker for Unsupervised Commonsense Question Answering

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Abstract

Without labeled question-answer pairs for necessary training, unsupervised commonsense question-answering (QA) appears to be extremely challenging due to its indispensable unique prerequisite on commonsense source like knowledge bases (KBs), which are usually highly resource consuming in construction. Recently pre-trained language models (PLMs) show effectiveness as an alternative for commonsense clues when they play a role of knowledge generator. However, existing work either relies on large-scale in-domain or out-of-domain labeled data, or fails to generate knowledge of high quality in a general way. Motivated by human thinking experience, we propose an approach of All-round Thinker (ArT) by fully taking association during knowledge generating. In detail, our model first focuses on key parts in the given context, and then generates highly related knowledge on such a basis in an association way like human thinking. Besides, for causal reasoning, a reverse thinking mechanism is especially added to further enhance bidirectional inferring between cause and effect. ArT is totally unsupervised and KBs-free. We evaluate it on three commonsense QA benchmarks: COPA, SocialIQA and SCT. On all scales of PLM backbones, ArT shows its brilliant performance and outperforms previous advanced unsupervised models. Our code is available at https://github.com/WangJW424/commonsenseQA-ArT.

Figure 1 gives a typical example. To select the correct cause of the fact “My body cast a shadow over the grass”, models should know that “Light is obscured to produce shadows” and “The sun emits light”. As human beings, we can immediately make this association and judgment because above knowledge is deeply branded in our mind due to daily seeing and hearing, and maybe long-term education, which is so-called commonsense. However, it could be much difficult for models to be equipped with such ability. Besides, commonsense QA usually takes an unsupervised setting which makes this task even more difficult. This setting means there is no labeled training data available as commonsense is too broad to build a sufficient labeled training dataset (Shwartz et al., 2020).

To deal with it, prior work focused on building large-scale knowledge bases (KBs), also known as knowledge graphs (KGs), which usually contain millions of nodes and edges to record the relation between entities as relation triple: \(<e_1, r, e_2>\) (Speer et al., 2017; Sap et al., 2019a). QA models then can be injected with commonsense through retrieving over KBs (Miller et al., 2016). Though impressive improvements are gained, such method is resource consuming in building or finding a

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1 Introduction

Commonsense question-answering (QA) has been a more challenging natural language understanding (NLU) task than conventional QA tasks, for it requires extra commonsense knowledge, which cannot be directly acquired from the given context, to make an appropriate answer (Niu et al., 2021).
good and suitable KB (e.g. Building ConceptNet needs 30 GB of RAM\textsuperscript{1}). Recently, pre-trained language models (PLMs) have been widely used and proved to be effective in commonsense QA (Niu et al., 2021; Xia et al., 2022). Thanks to the self-supervised pre-training strategy on large-scale unlabeled text (e.g. WebText (Radford et al., 2019) and Wikipedia\textsuperscript{2}), PLMs are competent for many tasks even under a zero-shot setting. And fine-tuning PLMs on task-specific data in a supervised way can further produce even stronger results (Schick and Schütze, 2021a; Gao et al., 2021; Schick and Schütze, 2021b). Since high-quality labeled datasets are rare, researching on unsupervised commonsense QA is still of great significance. With the help of PLMs, existing studies have explored some good solutions (Niu et al., 2021; Bosselut et al., 2021; Shwartz et al., 2020), however they either rely on large-scale in-domain or out-of-domain labeled data, or need to be specifically designed for different tasks. In this work, we focus on designing a simple and general method to solve commonsense QA tasks in a strictly unsupervised way.

Based on two empirical observations from human thinking,

(1) Given a question with context, people firstly tend to focus on several key parts (as marked in red in Figure 1) and then make corresponding associations to choose the right answer;

(2) For causal reasoning, people tends to carry out a bidirectional inferring to assist answer selection or verify the answer correctness.

we propose All-round Thinker (ArT) for unsupervised commonsense QA, which includes two principal methods: notes taking (NT) and reverse thinking (RT). Specifically,

(1) NT extracts some keyphrases out of the context and then generates corresponding notes, which will be added as extra knowledge in later evaluation. Based on an unsupervised keyphrase extractor, we designed our knowledge generation rule to be simple and general.

(2) RT converts the causal inferring question to two different forms: \(\text{cause} \rightarrow \text{effect}\) and \(\text{effect} \rightarrow \text{cause}\), and then integrates the decisions made from the two reverse directions.

Our proposed model is strictly unsupervised and KBs-free for all it needs is PLMs. We test ArT and validate its effectiveness on three commonsense QA benchmark datasets: COPA (Roemmele et al., 2011), SocialIQA (Sap et al., 2019b) and SCT (Mostafazadeh et al., 2016). Our contribution is summarized as follows:

- ArT can generate highly related knowledge through the imitation of human behaviour and thought, which is qualified with inherent interpretability.

- Compared with existing work, ArT is simple and general, which totally gets rid of the needs of any labeled data and the specific design on any specific task.

- We conduct experiments on 3 commonsense QA benchmarks with 4 different scales of PLMs, so as to reach solid and reproducible results. The results show that ArT outperforms other advanced unsupervised models.

2 Related Work

2.1 Building and Usage of Knowledge Bases

In order to equip QA models with commonsense reasoning ability, previous researches were devoted to building and retrieving large-scale knowledge bases (KBs). ConceptNet (Speer et al., 2017) is one of the most famous traditional KBs, which contains over 21 million edges (for relations) and over 8 million notes (for entities). While ATOMIC (Sap et al., 2019a) focuses more on if-then relations between events.

Previous work applies a relatively standard routine to solve commonsense QA. Given an existing KB, QA models can retrieve relation triples \(<e_1, r, e_2>\) over it, which can be injected into models as word embedding directly (Wang et al., 2014; Paul and Frank, 2019) or first converted to a complete sentence according to preset templates (e.g. \(<\text{bird}, \text{CapableOf}, \text{fly}>\rightarrow \text{Bird can fly.}\) and then integrated with the raw input text (Ma et al., 2019; Mihaylov and Frank, 2018; Bauer et al., 2018). This type of methods may give remarkable performance for commonsense QA (Weissenborn et al., 2017). However, building and retrieving of KBs are both resource consuming (Bosselut et al., 2021).

Bosselut et al. (2019) claimed that commonsense knowledge does not cleanly fit into a schema of comparing two entities with a known relation so
that they proposed COMET, which can generate rich and diverse commonsense descriptions in natural language. However, COMET has to extract knowledge triples from existing KBs as seed for PLM fine-tuning, while our method is totally KBs-free.

2.2 PLMs in Unsupervised Commonsense QA

Due to excellent performance and versatility, PLMs now dominate the backbone design of many NLP tasks, especially in QA (Wang et al., 2021; Zhang et al., 2021). Benefiting from the long-term pre-training on large-scale unlabeled text, PLMs are equipped with implicit or explicit commonsense (Davison et al., 2019). As a result, there comes a tendency to rely on PLMs as the sole source of world knowledge to solve commonsense QA in a zero-shot setting (Shwartz et al., 2020; Bosselut et al., 2021).

SEQA proposed by Niu et al. (2021) exploits generative PLMs to generate hundreds of pseudo-answers, and then applies Sentence-BERT (Reimers and Gurevych, 2019) to calculate semantic similarity between candidates and these generated pseudo-answers. A voting mechanism is designed to make final selection. Though SEQA shows impressive performance, it relies much on PLMs fine-tuned on large-scale labeled NLI (Natural Language Inference) datasets. Without such fine-tuning on such labeled datasets, SEQA’s effectiveness will sharply decline. Instead, our method relies nothing but vanilla PLMs.

Shwartz et al. (2020) proposed Self-talk, which creatively applies PLMs as commonsense generator. It uses preset question prefixes to firstly prompt the PLM to generate information seeking questions (ISQs). ISQs will be put back to secondly prompt the PLM to generate their answers as clarifications, which will work as knowledge in later evaluation. Though this method is strictly unsupervised, the question prefixes are not general and have to be carefully designed according to different tasks. Besides, Self-talk fails to generate knowledge of high quality since the generation of ISQs and clarifications are both erratic. Inspired by Self-talk and towards its shortage, we designed a general method to generate knowledge of high relevance.

2.3 Unsupervised Keyphrase Extraction

Keyphrase extraction (KE) is the task of selecting several words or phrases that can summarize the main topic of the document (Hasan and Ng, 2014). Unsupervised KE methods use different features of the document, such as word frequency, position feature, relationship between words, etc (Mihalcea and Tarau, 2004; Bougouin et al., 2013).

SIFRank (Sun et al., 2020) is one of the most advanced unsupervised keyphrase extractors. It leverages different features of words in document and evaluates the weight of candidate phrases according to word embedding provided by PLMs. SIFRank is originally designed to extract key noun phrases from given documents, and we made slight modifications to adapt it to our model.
Table 1: Note templates lookup table.

3 All-round Thinker

Inspired by the behaviour and thought of human beings during solving questions requiring commonsense, we propose All-round Thinker (ArT). Figure 2 gives its overview. We will firstly introduce the task definition and the basic solution, and then describe the two principal methods of ArT in detail: Notes Taking (NT) and Reverse Thinking (RT).

3.1 Task Definition and Basic Solution

This work focuses on unsupervised commonsense reasoning and overcome the shortage of Self-abstracted from PLMs. The final predicted answer is selected as:

\[
\hat{A} = \arg\max_{O^t} S(O^t|C, Q)
\]

3.2 Notes Taking

To make full use of PLMs’ potential of commonsense reasoning and overcome the shortage of Self-talk (Shwartz et al., 2020), we propose notes taking (NT) to generate commonsense descriptions in natural language (defined as “notes” in our work) in a simple and general way. NT is composed of two phases: keyphrase extraction and notes generation.

3.2.1 Keyphrase Extraction

Taking \(O^t\) and its corresponding \(C\) and \(Q\) as input (as shown in left bottom of Figure 2), ArT firstly rewrites the original interrogative \(Q\) into a declarative form (We followed the question rewriting method proposed by Shwartz et al. (2020)) and then concatenate \(<C, Q, O^t>\) as a statement (\(ST_O^t\)). Then, we use an unsupervised keyphrase extractor to extract keyphrases from \(ST_O^t\). To be specific, we extract three types of phrases: noun phrase (NP), verb phrase (VP) and person name phrase (PNP).

To implement this, for each type of phrase we designed a simple CFG (context-free grammar (Chomsky and Schützenberger, 1959)) rule to extract it out of the whole sentence, as following:

\[
\begin{align*}
NP & \rightarrow \text{(nn|adj)} * +nn \\
VP & \rightarrow vb + (pr) \{0, 1\} + NP \\
PNP & \rightarrow (pn) \{1, 2\}
\end{align*}
\]

where \(VP, NP\) and \(PNP\) are non-terminators; \(vb\) (verb), \(nn\) (noun), \(adj\) (adjective), \(pn\) (person name) and \(pr\) (preposition) are terminators; ‘+’ means concatenation; \(\{a, b\}\) means repetition times range from \(a\) to \(b\). ‘*’ is equivalent to \(\{0, \infty\}\).

Then, we add these CFG rules to the Regexp-Paser tool of NLTK (Bird, 2006). We will extract top 5 most important keyphrases without any label or fine-tuned model but word embeddings obtained from a PLM, i.e. ELMo (Peters et al., 2018).

3.2.2 Notes Generation

Once keyphrases are obtained, we can retrieve a preset note templates set for getting notes prefixes. Considering that: (1) For an object (NP), people will think “what is it” and “what is it for”; (2) For a behavior (VP), people will think “what does it mean” and “what is the cause/effect”; (3) For a person (PNP), people will think “who is he/she”
and “what is his/her feeling/motivation/reaction”, our proposed general-purpose note templates set is presented in Table 1.

We use the types of keyphrases as keys and templates lists as values to build the note templates set as a lookup table. Given such a lookup table, we can immediately retrieve the note templates for our extracted keyphrases and simply replace the tag ([NP], [VP] and [PNP]) with these keyphrases to form the note prefixes\(^3\). Though this lookup table seems to be simple, it shows effectiveness and generality on different benchmarks.

Next, for each note prefix, we will concatenate it to \( C \) and input them into a generative PLM to generate the complete note. Specifically, nucleic sampling (Holtzman et al., 2020) with \( p = 0.8 \) is applied as the decoding strategy rather than greedybeam search to increase the diversity of generated text. Meanwhile, to ensure the quality and scale the number of generated notes, we sort all the notes according to their perplexity estimated by the PLM. We denote this process as Rethinking.

Finally, we will retain top \( K \) notes to construct the notes set: \( \{note^k\}_{k=1}^K \), as shown in middle top of Figure 2. Each \( note^k \) will be inserted into \( ST_O \) as extra knowledge to assist later option scoring. The score of \( O^i \) w.r.t \( note^k \) is calculated as:

\[
score^{i,k}_O = P_{LM}(O^i|note^k + ST_O - O^i)
= \frac{1}{|O_i|} \sum_{t=1}^{|O_i|} \log P_{LM}(O^i_t|note^k + ST_O - O^i + O^i_{<t})
\]

(3)

in which ‘+’ means concatenation and ‘-’ means removing. Eventually, a voting mechanism is applied to integrate the scores w.r.t all notes as:

\[
Score^i_O = \frac{1}{K} \sum_{k=1}^K score^{i,k}_O
\]

(4)

It is worth noting that there is no need in training from any labeled data throughout NT. And there is no need to modify the note templates according to different tasks since our note templates is designed for general purpose.

3.3 Reverse Thinking

For causal reasoning questions, we additionally introduce reverse thinking (RT) which conducts a bidirectional inferring between cause and effect. To implement this, besides the ordered rewriting \( ST_R \) as mentioned in Section 3.2.1, we also apply reverse rewriting that concatenates them in the order of \( <O^i, Q_R, C> \) (denoted as \( ST_R \)), as shown in the right bottom of Figure 2. Note that \( Q_R \) is the opposite question of \( Q \). To be specific, after question rewriting, “Because” and “Therefore” are two opposite questions in causal reasoning tasks.

To conduct bidirectional inferring, except for \( Score^i_O \) as introduced in Section 3.2 for the ordered inferring: \( C + Q \rightarrow O^i \), we set another scoring function \( Score^i_R \) for reverse inferring: \( O^i + Q_R \rightarrow C \), as:

\[
Score^i_R = P_{LM}(C|ST_R - O^i)
= \frac{1}{|C|} \sum_{t=1}^{|C|} \log P_{LM}(C_t|ST_R - C + C_{<t})
\]

(5)

To take advantage of bidirectional inferring, we design a mixed scoring function by simply compute the average value of the above two:

\[
Score^i_X = \frac{1}{2}(Score^i_O + Score^i_R)
\]

(6)

Finally, formula (2) is applied to select the answer by replacing \( S \) with \( Score^i_O \) (default) or \( Score^i_X \) (for causal reasoning). From the perspective of model enhancing, averaging \( Score^i_O \) and \( Score^i_R \) can be regarded as the assembly of two models (“cause” model and “effect” model), which is a common method to enhance model performance and robustness.

4 Experiment

4.1 Datasets

ArT is evaluated on three different commonsense QA benchmarks: COPA (Roemmele et al., 2011), SocialIQA (Sap et al., 2019b) and SCT (Mostafazadeh et al., 2016). Here are the detailed information:

- COPA\(^4\) (Choice of Plausible Alternatives): evaluates the ability of causal reasoning about a certain event, which is described as a single sentence. Each question is accompanied with two candidate options.

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\(^3\)In order to keep a correct grammar, for VP we will firstly convert its verb into gerund form before replacing.

\(^4\)https://people.ict.usc.edu/~gordon/copa.html
• SocialIQA\(^5\) (Social Interaction Question Answering): evaluates the reasoning ability on social interactions. It has various questions, including the subject’s motivation, reaction, personality, etc. Each question is accompanied with three candidate options.

• SCT\(^6\) (Story Cloze Test): requires models to select the right ending of the given short story from two alternatives. Each story is composed of four sentences.

Since two test sets of the three datasets are hidden, we report all results on dev sets. Note that the labels are kept invisible and only used for final accuracy evaluating.

4.2 Baseline and Contrastive models

Our baseline is constructed as only using PLMs as scorer without any explicit knowledge injection. Formula (1) is applied as the scoring function as described in Section 3.1. We also compare ArT with other advanced unsupervised models:

• Self-talk\((\text{Shwartz et al., 2020})\): It acquires knowledge through a two-stage prompting of PLMs. Different question prefixes had to be specially designed for different tasks.

• SEQA\((\text{Niu et al., 2021})\): It applies PLMs to generate hundreds of pseudo-answers and compares them with each option. However, its scorer relies on PLMs fine-tuned on large-scale labeled NLI datasets, which is not strictly unsupervised. For fair comparison, we design another setting that replaces the fine-tuned PLM with the original one (only pre-trained on unlabeled text).

• CGA\((\text{Bosselut et al., 2021})\): It employs a generative KB COMET\((\text{Bosselut et al., 2019})\), which is trained on an existing seed KB (e.g. ConceptNet), to construct context-relevant knowledge graphs to reason over.

4.3 Setup

Following previous work, we employ OpenAI GPT\((\text{Radford et al., 2019})\) as the PLM backbone. To reach solid and reproducible results, we conduct experiments on GPT-2 of 4 different scales: distil, medium, large and xlarge. For ArT and Self-talk, the same scale GPT is applied during both knowledge generating and option scoring. For SEQA, GPTs of different scales are used for pseudo-answers generation and \text{SRoBERTa}_{\text{large}}\((\text{Reimers and Gurevych, 2019})\) is used for semantic similarity calculation. To distinguish, \text{SRoBERTa}_{\text{large}}\(\_\text{Origin}\) refer to \text{SRoBERTa}_{\text{large}} with and without further fine-tuning on NLI datasets, respectively. For Self-talk\(^7\) and SEQA\(^8\), we re-run their codes with their original settings and report both our re-running results\(^9\) and results coming from their publications. For CGA, we report results provided by Niu et al. (2021). For ArT, we modified the open source code of SIFRank\(^{10}\) to enable it to extract more kinds of phrases rather than only noun phrase. The size of notes set \((K)\) is set as 32 as default. Except for \text{Score}_{\text{O}}\, ArT takes another setting \text{Score}_{\text{X}} on COPA.

4.4 Results

Table 2 shows the results on three benchmarks. The results of our re-running is highly consistent with those reported in their publications (last column). Note that published results on COPA seem to have a deviation with our reproduction. It because that they are on test set, while ours on dev set. Shwartz et al. (2020) reported 66.0% on COPA in their paper, which is tested on the dev set of a small version which contains 1/5 instances of that other researches used. And ArT reaches 68.0% on that set under the same setting.

On all datasets, ArT obtains state-of-the-art performance among almost all fully unsupervised models. Besides, it is noticed that on GPT of different scales, ArT with NT stably brings positive improvement over baseline. On causal reasoning task COPA, adding RT will bring further accuracy improvement.

In contrast with ArT, Self-talk fails to maintain effectiveness, whose accuracy is even slightly lower than baseline from time to time, especially on SCT. It indicates that the knowledge generated by Self-talk could be noisy and as a result it misguides model evaluation.

With the help of \text{SRoBERTa}_{\text{large}}\(\_\text{NLI}\), SEQA can reach very impressive results on all the datasets, especially SCT (exceed all models than over 10%).

\(^5\)https://leaderboard.allenai.org/socialiqa
\(^6\)https://www.cs.rochester.edu/nlp/rocstories/
\(^7\)https://github.com/vered1986/self_talk
\(^8\)https://github.com/heyLinsir/Semantic-based-QA
\(^9\)For each setting except GPT-2\(\_\text{large}\) (limited by the computational power), we run 3 times and report the average number.
\(^{10}\)https://github.com/sunyilgdx/SIFRank
However, when working in a strictly unsupervised mode, this method quickly becomes invalid (close to random selection).

We also observe a common phenomenon on all our ArT, baseline and contrastive models: when enlarging GPT-2 from large (750M parameters) to xlarge (1500M parameters), we encounter no obvious model performance increasing and even decreasing in some scenarios. It indicates that there could be a limit to only using the method of increasing model parameters to improve the performance of language models as sentence scorer or knowledge generator.

5 Analysis and Discussion

5.1 Effect of Different Modules

In order to determine the source of performance growth, we conduct ablation study on ArT, as shown in Table 3. As expected, injecting knowledge with our NT has positive effect on all three tasks. When removing the Rethinking mechanism, all results slightly decrease, which indicates that Rethinking can help increase the quality of generated knowledge. Besides, $Score^l_X$ can bring further improvement whether or not NT is employed on COPA.

| Dataset | Models | COPA | SocialIQA | SCT |
|---------|--------|------|-----------|-----|
| Baseline | - | 56.8 | 45.9 | 69.1 |
| +Score^l_X | - | 68.9 | - | - |
| +NT | - | 67.0 | 47.6 | 69.5 |
| +NT – Rethinking | - | 66.2 | 46.7 | 69.4 |
| +NT + Score^l_X | - | 69.4 | - | - |

Table 3: Ablation study for ArT modules on GPT-2

5.2 Number of Notes and Keyphrases

Figure 3 shows the effect of notes set size $K$. On all the benchmarks, along with the increasing of $K$, the accuracy curves basically show an upward trend, which indicates that as the number of generated knowledge increases, ArT will not accumulate too much noise as Niu et al. (2021) observed in Self-talk. Therefore, compared with Self-talk, ArT tends to generate highly related knowledge, which is contributed by our NT mechanism.

In our experiments (Section 4), the number ($N$) of keyphrases to extract is set as 5 as default. To show the effect of $N$, we conduct an ablation study on SCT by setting $N \in \{1, 3, 5, 7, 9\}$. The PLM is selected as GPT-2$_{distil}$. Table 4 shows the results. It is noticed that extracting more keyphrases does
Figure 3: Accuracy curves of ArT on GPT-2 medium w.r.t the size $K$ of notes set.

| $N$ | baseline | ArT  |
|-----|----------|------|
| 1   | 59.6     | 59.6 |
| 3   |          | 60.0 |
| 5   |          | 60.2 |
| 7   |          | 60.2 |
| 9   |          | 60.0 |

Table 4: Accuracy (%) of ArT (GPT-2 distil) on SCT under different settings of $N$.

not always results in a better performance. But in general, the choice of $N$ does not have an obvious impact on the final performance.

| Dataset     | Model  | Rationality | Usefulness |
|-------------|--------|-------------|------------|
| COPA        | Self-talk | 0.24        | 0.20       |
|             | ArT     | **0.32**    | **0.28**   |
| SocialIQA   | Self-talk | 0.17        | 0.16       |
|             | ArT     | **0.26**    | **0.27**   |

Table 5: Human evaluation on the rationality and usefulness of generated knowledge.

### 5.3 Quality of Generated Knowledge

To compare the quality of generated knowledge (whether the knowledge is reasonable enough to be a “fact” and correlative enough to be useful), we conduct human evaluation on the rationality (-1: irrational, 0: meaningless, 1: rational) and usefulness (-1: negative, 0: neutral, 1: positive) of knowledge generated by ArT and Self-talk. Two annotators are asked to independently annotate 100 randomly selected knowledge for both COPA and SocialIQA. The overall average scores of two annotators for each dataset are shown in Table 5. It is noticed that ArT outperforms Self-talk in generating knowledge with both rationality and usefulness.

We further make statistics on the kinds of all the knowledge generated by Self-talk and ArT on COPA. We divide them into four classifications:

- **Positive**: Baseline makes the right prediction. Adding the knowledge still makes a right prediction.
- **Essential**: Baseline makes the wrong prediction. Adding the knowledge helps make a right prediction.
- **Invalid**: Baseline makes the wrong prediction. Adding the knowledge still makes a wrong prediction.
- **Negative**: Baseline makes the right prediction. Adding the knowledge leads to a wrong prediction.

As shown in Figure 4, by doubling Essential and reducing Negative knowledge, ArT outperforms Self-talk in generating high-quality commonsense.

Figure 5 and 6 in Appendix show some examples of knowledge generated by ArT, Self-talk and SEQA for COPA, SocialIQA and SCT. As can be seen, ArT generates highly related knowledge on the basis of focusing on keyphrases of given context. While Self-talk may generate meaningless or even noisy knowledge. It is also noticed that SEQA could generate very reasonable pseudo-answers. And to distinguish the relationship between these pseudo-answers and given options relies much on a sentence embedding extractor fine-tuned on labeled NLI data.

### 5.4 Effect of Note Types

As we designed three types of notes: NP, VP and PNP, we only consider one type at one time to show the effect of each in different benchmarks, as shown in Table 6 (The PLM is GPT-2 medium).

It is noticed that each type of notes has a positive effect when applied separately, and their combination works better. Note that COPA has no person
name phase (PNP), so PNP notes does not work on it. On SocialIQA, PNP works best among three
types of notes. This is reasonable since SocialIQA focus much on human behavior in social
interactions.

6 RT for Other Questions

Although RT is designed to enhance causal reasoning, we also explored if RT has the potential to help
other questions. To investigate this, we apply it on other two datasets: SocialIQA and SCT. Note that
in these tasks the opposite question is hard to de-
define, therefore we simply exchange the position of option and context, that is \( ST_O^i = < C, Q, O_i > \)
and \( ST_R^i = < O_i, Q, C > \). We employ three scoring functions on basis of GPT-2\textsubscript{medium} baseline, as shown in Table 7.

| Functions | COPA   | SocialIQA | SCT   |
|-----------|--------|-----------|-------|
| \( Score_O^i \) | 62.4   | 44.3      | 67.4  |
| \( Score_R^i \) | 63.2   | 42.5      | 62.8  |
| \( Score_X^i \) | 65.3   | 44.1      | 65.4  |

Table 7: Accuracy (%) of GPT-2\textsubscript{medium} baseline with different scoring functions.

On all the tasks, \( Score_O^i \) and \( Score_R^i \) can obtain positive results (much better than random selec-
tion). By simply averaging \( Score_X^i \), on COPA it can reach a higher score. On other tasks, it falls
into the middle of \( Score_O^i \) and \( Score_R^i \). Considering that \( Score_R^i \) shows a comparable performance with \( Score_O^i \) by simply exchanging the position of option and context, developing a general method for opposite question definition or designing a more exquisite method to integrate \( Score_O^i \) and \( Score_R^i \) perhaps could make RT suitable for questions beyond causal reasoning, which will be the key point of our future work.

7 Conclusion

Commonsense QA has been a challenging task for it requires extra knowledge beyond the given con-
text. In consideration of the high resource consumption of building knowledge bases (KBs) and the rarity of high-quality labeled data, this work aims at addressing commonsense QA in a fully KBs-free and unsupervised way. Inspired by the association process of human thinking, we propose All-round Thinker (ArT), which first focuses on key parts in the given context, and then generates highly related knowledge on such a basis in an association way. Besides, a reverse thinking mechanism is introduced to further enhance bidirectional infer-
ring for causal reasoning as human will do. We test ArT on three benchmarks: COPA, SocialIQA and SCT. ArT outperforms previous advanced unsupervised models and shows stable performance on all scales of PLM backbones.

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| COPA | SocialIQA |
|------|-----------|
| **Instance** | **Carson was excited to wake up to attend school.** |
| **C:** The woman hired a lawyer. | **Why did Carson do this?** |
| **Q:** What is the cause of this? | **a) Take the big test. b) Just say hello to friends. c) Go to bed early.** |
| **O:** a) She wanted to sue her employer. b) She decided to run for office. | **Carson felt great and enjoyed being around people again.** |
| **ArT** | **Carson did this because they wanted him in the classroom.** |
| **top-1:** After hiring a lawyer, she sued the man for sexual harassment. | **Attending school means working hard and learning something new everyday.** |
| **Self-talk** | **Carson did this because they wanted him there for his education.** |
| **top-1:** Before [b], the prosecutor said her client was a criminal. | **Carson felt great and enjoyed being around people again.** |
| **top-2:** “Lawyer” anyway is the word that I’m using to describe it. | **Carson felt great and enjoyed being around people again.** |
| **SEQA** | **To focus on his studies.** |
| **top-1:** She thought the employer was trying to rip her off. | **To play football with his friends and play street basketball.** |
| **top-2:** She was worried her employer would be fired. | **To focus on his studies.** |

Figure 5: Top two most contributing generated knowledge for instances of COPA and SocialIQA. The correct options are underlined. Keyphrases extracted by ArT are marked in red.

| SCT | ArT | Self-talk | SEQA |
|-----|-----|-----------|------|
| **Instance** | **Rick grew up in a troubled household. He never found good support in family, and turned to gangs. It wasn’t long before Rick got shot in a robbery. The incident caused him to turn a new leaf.** | **After turning a new leaf, he decided that fighting crime was more important than robbing banks.** | **He was now a good person.** |
| **C:** | **Rick is happy now.** | **Turning a new leaf means not committing any crimes again.** | **His life has dramatically improved with a period of rehabilitation and good mental health.** |
| **Q:** What is the ending of the story? | **b) Rick joined a gang.** | **Rick is happy now means that he has learned from his mistakes.** | **Carson did this because they wanted him there for his education.** |
| **O:** a) Rick is happy now. | **Top-1:** | **Rick is happy now means that he has learned from his mistakes.** | **Carson did this because they wanted him there for his education.** |
| **Self-talk** | **b) Rick joined a gang.** | **Rick is happy now means that he has learned from his mistakes.** | **Carson did this because they wanted him there for his education.** |
| **ArT** | **After turning a new leaf, he decided that fighting crime was more important than robbing banks.** | **Turning a new leaf means not committing any crimes again.** | **Carson did this because they wanted him there for his education.** |
| **top-2:** | **Turning a new leaf means not committing any crimes again.** | **Rick is happy now means that he has learned from his mistakes.** | **Carson did this because they wanted him there for his education.** |

Figure 6: Top two most contributing generated knowledge for instances of SCT. The correct options are underlined. Keyphrases extracted by ArT are marked in red.