Revisiting Generative Commonsense Reasoning: A Pre-Ordering Approach

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Abstract

Pre-trained models (PTMs) have lead to great improvements in natural language generation (NLG). However, it is still unclear how much commonsense knowledge they possess. With the goal of evaluating commonsense knowledge of NLG models, recent work has proposed the problem of generative commonsense reasoning, e.g., to compose a logical sentence given a set of unordered concepts. Existing approaches to this problem hypothesize that PTMs lack sufficient parametric knowledge for this task, which can be overcome by introducing external knowledge or task-specific pre-training objectives. Different from this trend, we argue that PTM's *inherent* ability for generative commonsense reasoning is underestimated due to the order-agnostic property of its input. In particular, we hypothesize that the order of the input concepts can affect the PTM's ability to utilize its commonsense knowledge. To this end, we propose a pre-ordering approach to elaborately manipulate the order of the given concepts before generation. Experiments show that our approach can outperform the more sophisticated models that have access to a lot of external data and resources.

1 Introduction

Pre-trained models (PTMs), such as BART (Lewis et al., 2020) and T5 (Raffel et al., 2020), have achieved significant progress in many natural language generation tasks. However, their ability to reason with common sense while generating text is questionable. To push research in this direction, Lin et al. (2020) proposed the task of generative commonsense reasoning (GCR), where the goal is to compose a fluent and rational sentence from a set of concepts. Figure 1 shows an example of this problem. To achieve this goal, the model must do commonsense reasoning to build connections between the given concepts and produce a logically sound sentence (e.g., it is the *pitcher* who throws the ball to the *batter* rather than the other way).

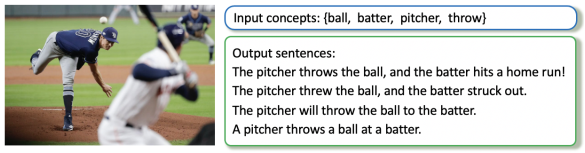

Figure 1: Example of the GCR task.

Prior works hypothesize that the vanilla PTMs are not capable of solving this challenging task (Liu et al., 2021; Fan et al., 2020; Zhou et al., 2021) partly because their self-supervised objectives do not explicitly capture the relational commonsense knowledge (Zhou et al., 2021). These works enhance the PTMs' performance by explicitly introducing knowledge during fine-tuning or implicitly teaching the model during further pre-training. However, we observe that in some cases, even without external knowledge, PTMs can create reasonable output for this task, indicating that PTMs may already have the commonsense reasoning ability to some degree. Therefore the challenge turns out to be how to make it easier for PTMs to fully utilize the inherent commonsense knowledge.

One potential solution of this challenge is to make the order of input concepts more natural and aligned with commonsense. For example, in Figure 1, taking $\{$*pitcher*, *throw*, *ball*, *batter*$\}$ as the input is better than $\{$*batter*, *throw*, *ball*, *pitcher*$\}$, since the order of concepts in the former input is more close to that in the outputs. Models that are not pre-trained, such as LSTM and GRU, prefer a pre-ordering of input tokens to align them with the (expected) output (Vinyals et al., 2016; Bisazza and Federico, 2016). For PTMs, recent works (Kale and Rastogi, 2020; Ribeiro et al., 2020; Hoyle et al., 2020) show that they can achieve reasonable performance on graph-to-text tasks without pre-ordering. However, the impact of pre-ordering on PTMs, in general, is not well analyzed.

In this work, we revisit PTMs' ability of generative commonsense reasoning *without access to external knowledge or task-specific pre-training*. We choose BART and T5, two state-of-the-art PTMs, as our underlying models. To analyze the utility of pre-ordering the concepts on models' performance, we introduce **Planned-BART** and **Planned-T5** to manipulate the input concept order before generation, which helps to make the order of input concepts more natural (more close to the order of concepts in the output sentence). We experimentally show that via pre-ordering, Planned-BART and Planned-T5 exceed the more sophisticated models that have access to external knowledge or training data. It indicates that PTM's inherent ability for generative commonsense reasoning was underestimated while a simple pre-ordering step can help PTMs better use this ability.

2 Related Works

2.1 Generative Commonsense Reasoning

There are two major approaches to enhance the vanilla PTM's ability of commonsense reasoning on generation. The first approach is to introduce explicit knowledge from external sources such as ConceptNet (Liu et al., 2021) and retrieved prototypes (Fan et al., 2020; Wang et al., 2021), which can facilitate GSR by either building connections between related concepts or providing adjunct words for the input. The second approach is to explicitly teach models to reason over the concepts via new pre-training objectives (Zhou et al., 2021). Different from these works, we examine PTMs' inherent ability of GSR without the help of external knowledge or task-specific pre-training.

2.2 Sequence Pre-Ordering

Previous works have shown that the pre-ordering of input sequence can improve the task of graph-to-text generation (Moryossef et al., 2019; Zhao et al., 2020), but they use non-pre-trained LSTM and the pre-ordering methods rely on rich structural information from the input. We instead focus on PTMs and non-structural input. For PTMs, Hessel and Schofield (2021) and Sinha et al. (2021) show that PTMs are resilient to shuffling the order of input tokens on the tasks of natural language understanding, but they didn't study the generation problem. Hoyle et al. (2020) show that a suitable pre-ordering can improve the generation quality. However, they didn't provide a general pre-ordering method for the problem of keywords-to-text generation.

3 Generative Commonsense Reasoning

3.1 Task Formalization

Given a set of lemmatized tokens representing concepts $\mathcal{X} = \{x_1, \cdots, x_m\}$, where each x_i can be a noun or a verb, the goal is to generate a fluent and grammatically correct English sentence $\mathbf{y} = \{y_1, \cdots, y_n\}$ such that it contains all of the concepts in $\mathcal{X}$. The task does not require x_i to have the same morphological form as it appears in $\mathbf{y}$. Figure 1 shows an example of the task. Note that $\mathcal{X}$ is an unordered set of concepts. We refer to a permutation of $\mathcal{X}$ as a *Plan* of the concept set. For a given output sentence $\mathbf{y}$, we re-order $\mathcal{X}$ to make the concepts have the same order as those in $\mathbf{y}$ and call it as the *Skeleton* of $\mathbf{y}$. Note that skeletons are associated with the outputs while plans are determined before generation. We refer to the plans which are identical to the references' skeletons as *Oracle Plans*.

We use BART and T5, two state-of-the-art PTMs, as the underlying generation models. Both models are based on the Transformer architecture (Vaswani et al., 2017). Similar to other sequence-to-sequence models, they receive $\mathbf{x} = \{x_1, \cdots, x_m\}$ as input, and model the probability of the output sequence $\mathbf{y} = \{y_1, \cdots, y_n\}$ as:

$$p(\mathbf{y} \mid \mathbf{x}; \boldsymbol{\theta}) = \prod_{t=1}^{|\mathbf{y}|} p\left(y_t \mid y_{1:t-1}, \mathbf{x}; \boldsymbol{\theta}\right). \quad (1)$$

3.2 Planned Model

To fine-tune PTMs on this task, previous works regard the input as an unordered set and use its random linearization as the input in both training and inference phase. Although it is trained in an order-agnostic setting, PTMs are naturally position-sensitive models because the same input words in different permutations have different positional representations.

Leveraging this property, we introduce Planned-BART and Planned-T5 to make both models aware of the input order by regarding the input as an ordered sequence. To order the input concepts properly, in the training phase, we re-order the concepts according to the corresponding oracle plan. That is, we force the order of concepts in both input and output sequences to be identical during training, which

Model \ Metrics	ROUGE-2/L		BLEU-3/4		METEOR	CIDEr	SPICE	Coverage
BART (Lin et al., 2020)	22.23	41.98	36.3	26.3	30.9	13.92	30.6	97.35
EKI-BART (Fan et al., 2020)	24.36	45.42	42.9	32.1	32.0	16.80	32.5	-
KG-BART (Liu et al., 2021)	23.38	44.54	42.1	30.9	32.4	16.83	32.7	98.68
Planned-BART (Ours)	24.97	46.13	44.8	34.1	32.9	17.47	33.1	98.99
T5 (Lin et al., 2020)	22.01	42.97	39.0	28.6	30.1	14.96	31.6	95.29
CALM (Zhou et al., 2021)	-	-	-	29.5	31.9	15.61	33.2	-
RE-T5 (Wang et al., 2021)	-	-	-	-	-	-	34.3	-
Planned-T5 (Ours)	24.07	46.11	44.6	33.7	32.8	17.60	34.0	98.60
Human Performance	48.88	63.79	48.2	44.9	36.2	43.53	63.5	99.31

Table 2: Automatic evaluation of generation quality. We compare our methods with pre-train- or knowledge-enhanced baselines. Our best model outperforms previous models on all automatic measures. The only exception is RE-T5, which uses both external knowledge and pre-training (with 7 times larger training data).

can better help the model utilize its inherent commonsense reasoning capabilities. In the inference phase, the oracle plans of concepts are unavailable. We instead obtain the plan using a *Planner*. Leveraging the power of PTMs, the planner is a vanilla BART or T5 model, which is fine-tuned on unordered (randomly linearized) input and produces a sentence as output. The skeleton of the planner's output forms the plan for planned models.

4 Experiments

4.1 Dataset and Evaluation

We conduct experiments on the CommonGen dataset (Lin et al., 2020), which contains 35k concepts-sentence pairs for training/validation/test. To build concepts-reference pairs, CommonGen first collects frequently co-occurring concepts from image captions. Each concept-set contains three to five concepts. The references in the training set are original captions while those in the validation and test sets are collected by crowd-sourcing.

The quality of the generated text is evaluated through several automatic metrics such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), CIDEr (Vedantam et al., 2015), and SPICE (Anderson et al., 2016). We also report Coverage (Lin et al., 2020), which is the average percentage of input concepts that are present in the output sentences.

4.2 Results

We compare the performance of our pre-ordered method with the unordered BART and T5, as well as two knowledge-enhanced BART models: EKI-BART and KG-BART, and two T5 models enhanced by further pre-training: CALM and RE-T5. Table 2 lists the results of automatic measures. The training details can be found in §1 of Appendix.

Our Planned-BART and Planned-T5 models outperform vanilla BART and T5 models, demonstrating that pre-ordering the input helps PTMs in effectively leveraging their inherent commonsense knowledge. Our models also outperform three out of four baselines that use external knowledge or pre-training objectives on all measures. The only exception is RE-T5, which is pre-trained with a seven times larger training data and enhanced by a BERT-based prototype retriever. This indicates that PTMs inherently contain a lot of commonsense knowledge that needs to be first utilized before bringing in information from external sources.

To further explore the potential of the pre-ordering method, we conduct another experiment to investigate the impact of concept orders on generation quality. Given a test concept set, we feed all of its permutations to either BART or Planned-BART to generate sentences. We then rank the sentences according to their probabilities in Equation 1 and pick the most probable sentence as the final output. We refer to the methods using this strategy as BART $_{\text{Rank}}$ and Planned-BART $_{\text{Rank}}$, respectively. Note that the ranking method is computationally inefficient. In this work we only use these models to provide an estimate of the upper bound on the performance of the pre-ordering method.

As shown in Table 2, the performance of Planned-BART is close to its ranking variant, Planned-BART$_{\text{Rank}}$. This demonstrates the effectiveness of our planning strategy – it helps Planned-BART achieve a performance comparable to the upper-bound at a much lower computational overhead. We also observe that Planned-BART $_{\text{Rank}}$ achieves better scores than BART $_{\text{Rank}}$. This is because Planned-BART is trained on oracle plans, which helps it in better utilizing its inherent commonsense knowledge.

Model \ Metrics	R-2	B-4	M	C	S
Planned-BART	24.97	34.1	32.9	17.47	33.1
BART$_{\text{Rank}}$	24.31	33.0	33.0	17.39	33.2
Planned-BART$_{\text{Rank}}$	25.04	35.0	33.3	17.89	33.6

Table 2: Evaluation of Planned-BART and ranking models on ROUGE-2, BLEU-4, METEOR, CIDEr, and SPICE.

Model \ Metrics	RATION	FLUENCY	SUCCINCT
BART	-0.38	-0.33	-0.56
BART$_{\text{Rank}}$	-0.10	0.04	-0.13
Planned-BART	-0.29	-0.19	-0.17

Table 3: Results of human evaluation on rationality, fluency, and succinctness. We report the pair-wise scores between Planned-BART$_{\text{Rank}}$ (the best model) with three other models. Negative scores indicates worse performance compared with Planned-BART$_{\text{Rank}}$.

4.3 Human Evaluation

We randomly select 100 test instances and evaluate the generation quality of a system according to Rationality, Fluency, and Succinctness as in Liu et al. (2021). We conduct a pairwise comparison between Planned-BART$_{\text{Rank}}$ (the best model) with our three other methods[1]. For each test instance, we obtain the output sentences from two different models, and then ask three workers on Amazon Mechanical Turk to compare the two sentences according to the three measures listed above. More details can be found in §2 of Appendix.

Table 3 lists the results, where negative scores indicate worse performance compared with Planned-BART$_{\text{Rank}}$. The original BART performs the worst on all measures, while Planned-BART achieves closer quality to BART$_{\text{Rank}}$ and Planned-BART$_{\text{Rank}}$. These results are consistent with those of automatic evaluations and support our claim that Planned-BART can be a reasonable trade-off between performance and efficiency.

4.4 Impact of Permutation

We further investigate the impact of input permutation on the generated text. We find that the unordered models suffer from the repetition of content in the output. For example, in 34.2% of test cases, there is at least one concept that appears more than once in the output of the unordered BART. However, this percentage decreased to 3.2% for the output of Planned-BART. It is because that the decoder of Planned-BART can assign attention weights monotonically to the input, and reduce the repetition caused by re-attending the previous concepts. In Appendix §3 we provide a visualization of how the input order can impact the attention weights during decoding.

[1] We cannot compare with other baselines since their codes are not public or differ greatly from the method in the paper.

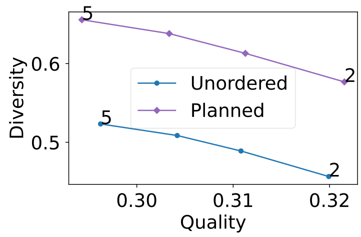

Figure 2: The quality-diversity plot of BART$_{\text{Rank}}$ and Planned-BART$_{\text{Rank}}$. With little degradation of quality, Planned-BART creates more diverse output compared with unordered BART.

We also find that in 94% of the cases, the output skeleton of Planned-BART is consistent with the order of input concepts. This order consistency allows us to have more control on output by adjusting the input concept order. Different orders can help the encoder to capture diverse commonsense relations between concepts and create diverse outputs. While unnatural diversity may hurt generation quality, we use SPICE as the measure for quality and BLEU-based discrepancy (Shu et al., 2019) for diversity, and evaluate the performance of BART$_{\text{Rank}}$ and Planned-BART$_{\text{Rank}}$ by selecting the top 2 to 5 candidates as outputs. Figure 2 shows the quality-diversity plot of two models. It indicates that with little degradation of generation quality, Planned-BART$_{\text{Rank}}$ can create more diverse output than BART$_{\text{Rank}}$. Appendix §4 shows an example.

5 Conclusion

In this work, we revisit the PTM's inherent ability of generative commonsense reasoning. We use BART and T5 as underlying generators and propose their planned variants to manipulate the order of the given concepts before generation. Experiments on COMMONGEN dataset demonstrate that this simple pre-ordering approach can outperform the previous pre-trained or knowledge-enhanced models. Besides that, planned models can leverage the pre-ordered concepts to create more succinct and diverse sentences. In conclusion, our work suggests that PTM's inherent ability for generative commonsense reasoning is underestimated due to the unordered input, and the pre-ordering step can help PTMs to improve the generation quality.

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A Training Details

The BART and T5 models are implemented using the Transformers library. We fine-tune each model on the training data of COMMONGEN with Adam. We set the learning rate as 2e-5 and adopt early stopping based on the loss of development set. The batch size of training is 64.

B Human Evaluation Details

We randomly select 100 test instances that had 5 concepts as input, since they are more challenging than those with fewer concepts. The three measures we used are 1) Rationality: whether or not the sentence is in accordance with commonsense; 2) Fluency: whether or not the sentence is fluent and has no grammatical errors; and 3) Succinctness: whether or not the sentence contains redundant words or repeated information.

The pairwise scores of those measures are calculated as follows. When comparing a certain approach to Planned-BART $_{\text{Rank}}$, we report the percentage of instances that were judged to be worse/better/same than those of Planned-BART $_{\text{Rank}}$, yielding a score ranging from -1 (unanimously worse) to 1 (unanimously better). For example, when evaluating the rationality scores, Unordered-BART $_{\text{Vanilla}}$ performs better/worse/same than Planned-BART $_{\text{Rank}}$ for 27%/65%/8% of the instances, yielding a pairwise score as 0.27-0.65=-0.38.

C Impact on Repetition

The repetition of the unordered BART is caused by the order-agnostic property of its input. Since the input concepts are unordered, the decoder cannot pay attention to the input in a monotonic way (from left to right) during decoding, which may mislead the decoder to attends to the concepts that have been previously generated. For example, on the left of Figure 3, the decoder attends to "tea" and "glass" twice during decoding, which achieves the local coherence but causes the global repetition issue and unnatural text. However, when modifying the input in another order, as shown in the right of Figure 3, the repetitive and unnatural expressions disappear. It indicates that the BART decoder has difficulty ordering the input globally, and providing a well-ordered plan as input can alleviate this issue. On the contrary, in Planned-BART, the decoder can assign attention weights monotonically to the input, and therefore reduce the repetition caused by re-attending the previous concepts.

Figure 3: The cross-attention matrix of two permutations of the same concept-set produced by unordered BART. It's difficult for Unordered-BART to learn the optimal order of attention.

D Impact on Diversity

Table 4 provides an example with the outputs created by both models and humans. Unordered-BART $_{\text{Rank}}$ can create only one output. Also, the object of *watch* is missing in it's output. On the other hand, the output of Planned-BART is more natural and diverse.

Model	Output	Skeleton
Unordered-BART	A crowd of people watch and dance to the music.	crowd watch dance music
Planned-BART	A crowd of people are dancing to music while others watch.	crowd dance music watch
	A man plays music and watches the crowd dance.	music watch crowd dance
	A group of people dance to music as a crowd watches.	dance music crowd watch
	A man watches a crowd of people dancing to music.	watch crowd dance music
Human	The crowd likes to watch her dance to the music.	crowd watch dance music
	The crowd watched the dance, and listed to the music.	crowd watch dance music
	I watched as the crowd dance to the music.	watch crowd dance music
	A person dancing to the music as a crowd of people watch.	dance music crowd watch

Table 4: Sample texts generated by Unordered-BART, Planned-BART, and humans for the concept set {dance, music, crowd, watch}. The diversity of Planned-BART is more close to human generation.