Revisiting Generative Commonsense Reasoning: A Pre-Ordering Approach

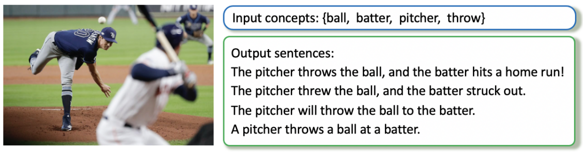
Chao Zhao[1] **Faeze Brahman**[2] **Tenghao Huang**[1] **Snigdha Chaturvedi**[1]
{zhaochao, tenghao, snigdha}@cs.unc.edu faezeb@allenai.org
[1] UNC Chapel Hill [2] Allen Institute for AI

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).



Input concepts: {ball, batter, pitcher, throw}

Output sentences:
The pitcher throws the ball, and the batter hits a home run!
The pitcher threw the ball, and the batter struck out.
The pitcher will throw the ball to the batter.
A pitcher throws a ball at a batter.

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., 2021; Hoyle et al., 2021) 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 ex-*

Findings of the Association for Computational Linguistics: NAACL 2022, pages 1709 - 1718
July 10-15, 2022 ©2022 Association for Computational Linguistics

ternal 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. (2021) 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 phases. 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 can better help the model utilize its inherent commonsense reasoning capabilities. In the inference phase, the oracle plans of concepts are unavailable.

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 1: 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).

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 [1] 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 1 lists the results of automatic measures. The training details can be found in Appendix A.

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. The only exception is RE-T5, which is further pre-trained.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. 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.

4.3 Human Evaluation

We randomly select 100 test instances and evaluate the generation quality of a system according

[1] Code is available at https://github.com/zhaochaocs/Planned-PTM

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 $_{\text{Rank}}$.

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.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 Appendix B.

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.

5 Analysis

In this section, we analyze the impact of input permutation on the model and the generated sentences.

5.1 Permutation Invariance

We first examine how the output changes when the original BART (which we refer to as Unordered-BART for clarity) and Planned-BART receive all possible permutations of concepts as input. We compare the skeleton of Planned-BART's outputs with the input plans and find that the output skeleton is consistent with the order of input concept in 94% of the cases, which is as expected.

In contrast, for Unordered-BART, we find that for 61% of the permutations, it can organize the concepts in one particular order irrespective of the input order. More details are provided in Appendix C. This observation suggests that Unordered-BART is permutation-invariant to the input to some degree. However, it is difficult for the model to be entirely insensitive to the input permutation, which explains the performance difference between BART and BART $_{\text{Rank}}$: a ranking strategy helps select a more suitable permutation of input and can therefore improve the generation quality.

5.2 Impact of Permutation on Encoding

The observations in Section 5.1 prompt a question about how Unordered-BART and Planned-BART have different behaviors when receiving input permutation. Here, we explore this question by studying the impact of input permutation on the model encoder, especially the global attention distributions and the local attention strength between certain word pairs.

One possible reason for the permutation invariance of Unordered-BART is that although different input plans have different positional embeddings and may affect hidden states of the lower layers, the encoder can build stable association among tokens at the higher layers, alleviating the disturbance from positional embeddings. For example, the model may know that people should "ride a bike on trail" even when the concept order is {ride, trail, bike}. We measure the word association inside the encoder using the strength of attention weights between concepts.

To verify our assumption, we calculate (i) the Jensen–Shannon divergence (JSD) of the encoder attention distributions w.r.t. all possible permutations of the input, and (ii) the variance of encoder hidden states w.r.t. the input permutations. Figure 2 shows the layer-wise JSD and variance averaged over the test set. For comparison, we also include the results from a randomly-initialized BART and the pre-trained BART (without fine-tuning).

From Figure 2 we observe that the attention distributions of Planned-BART have high JS divergence at each layer, and have a similar trend compared with that of Pre-trained BART. It indicates that attention distributions of these two models are affected by the input permutation, which is expected since their input is well ordered during pre-training or fine-tuning. As a result, the variances of hidden states on both models increase with a growth in layer depth. In contrast, the JS

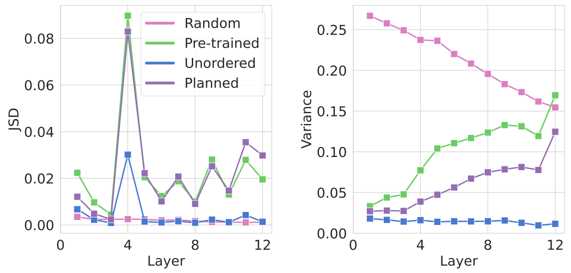


Figure 2: Left: JS divergence of encoder attention distributions w.r.t. the input permutations. Right: the variance of encoder hidden states w.r.t. input permutations.

divergence of attention in Unordered-BART gets close to 0 starting from layer 2 and becomes similar to that of the randomly initialized model. It indicates that the encoder can assign stable attention distributions to the input despite the difference in permutation. Because of this, the variances of hidden states on these two models decrease as the layer goes deeper. It partially explains the permutation invariance of Unordered-BART. We also noticed a substantial negative correlation between the variance of the encoder output and the percentage of the mode sentence (Spearman's $\rho = -0.435$), which supports our explanation.

In addition to the analysis of global attention distribution, we also investigate local attention patterns, i.e., whether the attention weights between concept tokens can reflect their commonsense relations. More details are listed in Appendix D. We find that compared with a randomly-initialized BART, the pre-trained BART is better at tracking commonsense relations of concepts despite input permutation, and fine-tuning can further strengthen this capability. We also find that the model heavily relies on the tracking ability when generating texts. It demonstrates that BART has the commonsense reasoning ability to some degree, and it is reasonable to leverage the output of Unordered-BART to obtain the plan for planned-BART.

5.3 Impact of Permutation on Decoding

In this section, we discuss how the input permutation can affect the quality of decoding output. Particularly, we show that reasonable planning can create less repetitive and more diverse output.

First, 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 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 E, we provide a visualization of how the input order can impact the attention weights during decoding.

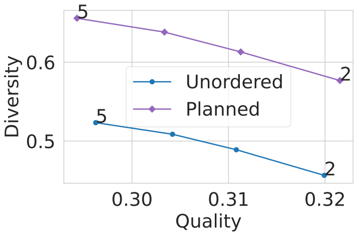


Figure 3: The quality-diversity plot of Unordered-BART $_{\text{Rank}}$ and Planned-BART $_{\text{Rank}}$.

Second, the order consistency between inputs and outputs in Planned-BART also allows us to have more control over output skeletons 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 Unordered-BART $_{\text{Rank}}$ and Planned-BART $_{\text{Rank}}$ by selecting the top 2 to 5 candidates as outputs. Figure 3 shows the quality-diversity plot of two models. It indicates that with little degradation of generation quality, Planned-BART can create more diverse output than Unordered-BART. We show an example in Appendix F.

6 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.

References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. Spice: Semantic propositional image caption evaluation. In *European conference on computer vision*, pages 382–398. Springer.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization*, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Arianna Bisazza and Marcello Federico. 2016. A Survey of Word Reordering in Statistical Machine Translation: Computational Models and Language Phenomena. *Computational Linguistics*, 42(2):163–205.

Kevin Clark, Urvashi Khandelwal, Omer Levy, and Christopher D. Manning. 2019. What does BERT look at? an analysis of BERT's attention. In *Proceedings of the 2019 ACL Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP*, pages 276–286, Florence, Italy. Association for Computational Linguistics.

Zhihao Fan, Yeyun Gong, Zhongyu Wei, Siyuan Wang, Yameng Huang, Jian Jiao, Xuanjing Huang, Nan Duan, and Ruofei Zhang. 2020. An enhanced knowledge injection model for commonsense generation. In *Proceedings of the 28th International Conference on Computational Linguistics*, pages 2014–2025, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Jack Hessel and Alexandra Schofield. 2021. How effective is BERT without word ordering? implications for language understanding and data privacy. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)*, pages 204–211, Online. Association for Computational Linguistics.

Alexander Miserlis Hoyle, Ana Marasović, and Noah A. Smith. 2021. Promoting graph awareness in linearized graph-to-text generation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 944–956, Online. Association for Computational Linguistics.

Phu Mon Htut, Jason Phang, Shikha Bordia, and Samuel R Bowman. 2019. Do attention heads in bert track syntactic dependencies? *arXiv preprint arXiv:1911.12246*.

Mihir Kale and Abhinav Rastogi. 2020. Text-to-text pre-training for data-to-text tasks. In *Proceedings of the 13th International Conference on Natural Language Generation*, pages 97–102, Dublin, Ireland. Association for Computational Linguistics.

Diederik P. Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 7871–7880, Online. Association for Computational Linguistics.

Bill Yuchen Lin, Wangchunshu Zhou, Ming Shen, Pei Zhou, Chandra Bhagavatula, Yejin Choi, and Xiang Ren. 2020. CommonGen: A constrained text generation challenge for generative commonsense reasoning. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 1823–1840, Online. Association for Computational Linguistics.

Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.

Ye Liu, Yao Wan, Lifang He, Hao Peng, and Philip S Yu. 2021. Kg-bart: Knowledge graph-augmented bart for generative commonsense reasoning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35.

Paul Michel, Omer Levy, and Graham Neubig. 2019. Are sixteen heads really better than one? In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 14014–14024.

Amit Moryossef, Yoav Goldberg, and Ido Dagan. 2019. step-by-step: Separating planning from realization in neural data-to-text generation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2267–2277.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21:1–67.

Leonardo F. R. Ribeiro, Martin Schmitt, Hinrich Schütze, and Iryna Gurevych. 2021. Investigating pretrained language models for graph-to-text generation. In *Proceedings of the 3rd Workshop on Natural Language Processing for Conversational AI*, pages 211–227, Online. Association for Computational Linguistics.

Raphael Shu, Hideki Nakayama, and Kyunghyun Cho. 2019. Generating diverse translations with sentence codes. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1823–1827, Florence, Italy. Association for Computational Linguistics.

Koustuv Sinha, Robin Jia, Dieuwke Hupkes, Joelle Pineau, Adina Williams, and Douwe Kiela. 2021. Masked language modeling and the distributional hypothesis: Order word matters pre-training for little. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing*, pages 2888–2913, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2015, Boston, MA, USA, June 7-12, 2015*, pages 4566–4575. IEEE Computer Society.

Oriol Vinyals, Samy Bengio, and Manjunath Kudlur. 2016. Order matters: Sequence to sequence for sets. In *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*.

Han Wang, Yang Liu, Chenguang Zhu, Linjun Shou, Ming Gong, Yichong Xu, and Michael Zeng. 2021. Retrieval enhanced model for commonsense generation. In *Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021*, pages 3056–3062, Online. Association for Computational Linguistics.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Remi Louf, Morgan Funtowicz, Joe Davison, Sam Shleifer, Patrick von Platen, Clara Ma, Yacine Jernite, Julien Plu, Canwen Xu, Teven Le Scao, Sylvain Gugger, Mariama Drame, Quentin Lhoest, and Alexander Rush. 2020. Transformers: State-of-the-art natural language processing. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 38–45, Online. Association for Computational Linguistics.

Hongming Zhang, Xin Liu, Haojie Pan, Yangqiu Song, and Cane Wing-Ki Leung. 2020. ASER: A large-scale eventuality knowledge graph. In *WWW '20: The Web Conference 2020, Taipei, Taiwan, April 20-24, 2020*, pages 201–211. ACM / IW3C2.

Chao Zhao, Marilyn Walker, and Snigdha Chaturvedi. 2020. Bridging the structural gap between encoding and decoding for data-to-text generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 2481–2491, Online. Association for Computational Linguistics.

Wangchunshu Zhou, Dong-Ho Lee, Ravi Kiran Selvam, Seyeon Lee, and Xiang Ren. 2021. Pre-training text-to-text transformers for concept-centric common sense. In *International Conference on Learning Representations*.

A Training Details

The BART and T5 models are implemented using the Transformers library (Wolf et al., 2020). We fine-tune each model on the training data of CommonGen with Adam (Kingma and Ba, 2015). 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 better/worse/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 Permutation Invariance

To figure out to what extent Unordered-BART is permutation-invariant, we conduct the following analysis. For each test instance, we feed all different input permutations to the Unordered-BART to obtain the corresponding output sentences. We measure the invariance of the outputs by computing the percentage of the most frequent output. If the concept order does not affect the output, all different permutations will lead to identical outputs and the percentage will be 100%. If half of the permutations obtain the same outputs, the percentage will be 50%. We measure the input invariance at the following two levels.

Sentence-level invariance For various permutations of a specific concept-set, if the percentage of the most frequent sentence is greater than an invariance threshold α, we regard the model as input-invariant to that instance at the sentence level.

Skeleton-level invariance The sentence-level invariance requires the output sentences to be identical, which is strict and does not consider minor lexical differences (e.g., the difference in function words or modifiers). Therefore, we also report the skeleton-level invariance by measuring the percentage of the most frequent skeleton (mode skeleton). It reflects whether or not the model output will follow a certain order under different permutations, which is a more forgivable invariance measure compared to its sentence-level counterpart.

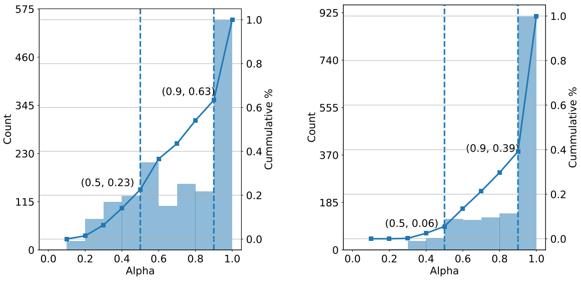


Figure 4: The histogram of COMMONGEN test set w.r.t. the percentage of most frequent sentences (left) and skeletons (right), respectively. We also show the cumulative distribution in blue lines. When $\alpha = 0.9$, 37% and 61% of the test instances are invariant at the sentence and skeleton-level, respectively.

Figure 4 shows the distribution of COMMONGEN test set w.r.t. the percentage of most frequent sentences (left) and skeletons (right). When setting $\alpha = 0.9$, 37% of the test instances are invariant at the sentence level, and 61% are invariant at the skeleton level. This indicates that for 61% of the permutations, Unordered-BART can organize the concepts in one particular order irrespective of the input order.

Relation	Head	UAS	I_{lh}
v-dobj-n	10-7	83.97	13
v-prep-adp-pobj-n	10-7	82.61	13
n-nsubj-v	11-12	87.62	3
n-prep-adp-pobj-n	10-8	60.55	15
v-advcl-v	4-11	85.37	4
v-conj-v	10-1	83.07	2
n-nsubj-v-dobj-n	6-16	62.34	40
v-xcomp-v	8-15	91.32	19
n-conj-n	10-0	88.75	56
n-comp-n	1-8	83.31	24

Table 4: The functional heads for each relation, as well as the corresponding UAS and importance rank.

D Analysis of Local Attention

In addition to the analysis of global attention distribution, we also investigate local attention patterns, i.e., the attention weights between concept tokens. Previous works show that some attention heads can reflect certain aspects of syntactic and semantic relations between words (Clark et al., 2019; Htut et al., 2019). We want to investigate if the heads can track commonsense relations between concepts.

For this purpose, we first build gold relations between the concepts that capture commonsense knowledge. One option is to utilize ConceptNet relations between concepts (Lin et al., 2020). However, these relations connect only two concepts at a time disregarding the context information from other concepts. Consider {throw, catch, dog, frisbee} as an example. "Dog" may be "caught" but this relation is less plausible in this case because of the existence of "frisbee". When considering this context, humans provide references such as "The dog catches the frisbee when the boy throws it."

Another option is to use the dependency relations between words in the reference sentences, which can capture the commonly occurring relations between concepts while incorporating the context. For example, the relation "catch$\xrightarrow{\text{dobj}}$frisbee" captures the commonsense that frisbee is often caught, Similar ideas are also adopted in Zhang et al. (2020). In particular, we extract the one-hop and two-hop dependency relations of all concept pairs from the references, and only keep the relations that appear in two or more references.

For attention probing, we use attention weights between input tokens to reflect the strength of their associations. Given two concepts c_i and $c_{j,j>i}$, we regard them as strongly associated under the attention head (l, h) if the attention weight $\alpha_{ij}^{l,k}$ is the highest among the scores from all the other concepts $c_{k\setminus\{i,j\}}$ to c_j.

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 5: 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.

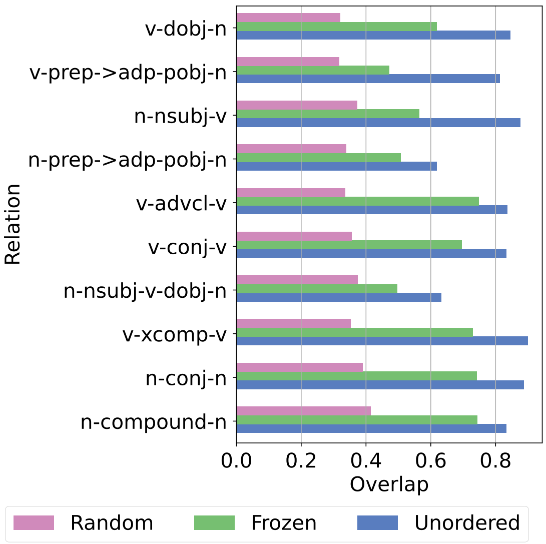


Figure 5: UAS of commonsense relations from three BART models via attention probing. The performance of fine-tuned Unordered-BART > pre-trained Frozen-BART > randomly-initialized BART among all of the relations.

We choose the 10 most common dependency relations from the test set and report the Unlabeled Attachment Score (UAS) of attention probing in Figure 5. We also list the UAS of a randomly initialized BART and a pre-trained BART without fine-tuning for comparison.

Results in Figure 5 show that for some frequent and simple relations such as "v-dobj-n" and "n-nsubj-v", there is at least one attention head that tends to track them regardless of the differences in the permutation orders. For example, attention head "Layer-10 Head-7" tracks the "v-dobj-n" relation with a UAS of 83.9%. The comparison among the three models shows that the pre-trained BART already exceeds the randomly initialized model in tracking commonsense relations between words, and fine-tuning further strengthens those relations.

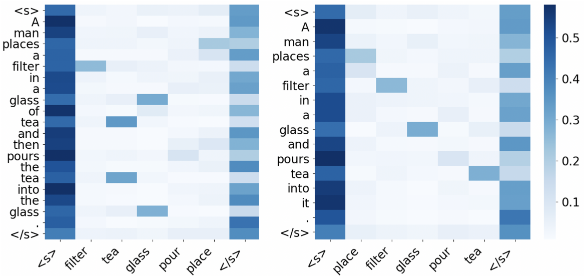


Figure 6: The cross-attention matrix of two permutations of the same concept-set produced by Unordered-BART. It's difficult for Unordered-BART to learn the optimal order of attention.

To demonstrate that these functional heads are important for generation, we use the expected sensitivity (Michel et al., 2019) of the model to each head to evaluate the head importance as

$$I_{lh} = \mathbb{E}_{x \sim X} \left| \frac{\partial \mathcal{L}(x)}{\partial \xi_{lh}} \right| \quad (2)$$

where $\mathcal{L}(x)$ is the loss of generation and ξ_{lh} is the mask variable for head $l - h$ with values in $\{0, 1\}$. The general idea is that the value change of important heads can have a larger impact on the model loss. Results are shown in Table 4. For most relations, the corresponding functional heads also have a high rank of importance. This consistency indicates that the model heavily relies on these heads when generating texts, and further demonstrates that the finetuned BART can capture the commonsense between concepts for generation.

E 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 attend to the concepts that have been previously generated. For example, on the left of Figure 6, 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 6, 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.

F Impact on Diversity

Table 5 provides an example with the outputs created by both models and humans. Unordered-BART can create only one output due to the permutation invariance. Also, the object of *watch* is missing in its output. On the other hand, similar to the human-written output, the output of Planned-BART is more natural and diverse.