Constrained Text Generation with Global Guidance – Case Study on CommonGen

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Abstract

This paper studies constrained text generation, which is to generate sentences under certain pre-conditions. We focus on CommonGen, the task of generating text based on a set of concepts, as a representative task of constrained text generation. Traditional methods mainly rely on supervised training to maximize the likelihood of target sentences. However, global constraints such as common sense and coverage cannot be incorporated into the likelihood objective of the autoregressive decoding process. In this paper, we consider using reinforcement learning to address the limitation, measuring global constraints including fluency, common sense and concept coverage with a comprehensive score, which serves as the reward for reinforcement learning. Besides, we design a guided decoding method at the word, fragment and sentence levels. Experiments demonstrate that our method significantly increases the concept coverage and outperforms existing models in various automatic evaluations.

1 Introduction

With the rise of deep learning methods, the task of natural language generation has received a surge of research interests (Gatt and Krahmer, 2018; Reiter and Dale, 2000). Sequence to sequence models have been used for meaning-to-text generation (Song et al., 2020, 2018; Damonte and Cohen, 2019), data-to-text generation (Puduppully et al., 2019) and text-to-text generation tasks such as abstractive summarization (Liu and Lapata, 2019; Tan et al., 2017) and machine translation (Sutskever et al., 2014; Bahdanau et al., 2015). The typical model is trained using a given set of output texts, using a cross-entropy loss to maximize the probability of each token given its preceding text. In other words, models are trained to mimic a “standard” human-written token sequence.

While such methods have been shown effective, they intuitively can be limited by forcing one correct answer on the model for each input. In contrast, the nature of languages suggests that there can be a range of different ways of expressing the same meaning. As a result, one solution can be to allow a model to generate outputs in freedom, giving feedback on the output quality. The recent investigation of human rewards on text summarizers (Stiennon et al., 2020) shows that such methods can largely outperform traditional methods.

While human feedback can be highly costly to obtain, we consider automatic ways for collecting feedback. In particular, we focus on constrained text generation, which constructs sentences under certain pre-conditions such as content (Lin et al., 2019), style (Shen et al., 2017) and topics (Feng et al., 2018; Wang et al., 2019b). In the broadest sense, most text generation tasks are constrained tasks. For example, the constraints for machine translation includes fluency and adequacy. Therefore our investigation can be generalized.

We focus on a commonsense text generation task (Lin et al., 2019), which asks the model to generate a natural text description given a set of common concepts. For example, if the input concept set is \{kid, room, dance\}, a plausible output sentence is “The kid loves to dance in her own room.”. To accomplish such a task, a generation model should understand the correlation between the given concepts and insert necessary words to produce a fluent sentence. As there can be different ways to interpret the correlation between the input concepts, the corresponding output sentence is not unique in terms of both meaning and phrasing. Thus the task provides a convenient playground for investigating reward-based training.

There are three main constraints for the task. First, the output should be fluent and grammatical. Second, the sentence should follow common sense. Third, The output should contain as many input
concepts as possible. Correspondingly, we consider three automatic measures of quality, namely fluency, common sense and concept coverage. For fluency, we measure the perplexity of output sentences using GPT-2 (Mager et al., 2020) assuming that fluent sentences have low perplexity. For measuring common sense, we fine-tune GPT-2 with ConceptNet (Speer et al., 2017), by following Wang et al. (2019a). Coverage is estimated by simple string matching.

The three types of automatic rewards are used to tune a UniLM (Dong et al., 2019; Bao et al., 2020) model, which is a sequence to sequence method built on Transformer (Vaswani et al., 2017). In particular, we first train a model by following the traditional method, maximizing the likelihood of a given set of human-written outputs. After obtaining the traditional model to its optimal performance, we use reinforcement learning (Williams, 1992) to further tune the parameters using the above rewards. This allows the system to freely generate outputs, receive feedback, and correct itself accordingly.

In addition, we design a guided decoding method at three levels: word, fragment, and sentence. At the word level, the generative model and the GPT-2 work together to predict the next word. At the fragment level, we construct a extra beam to save sentence fragments with the highest scores. At the sentence level, the score is used to re-rank the sentences produced by beam search.

Our experiments demonstrate that the guided training and decoding processes effectively improve the generation performance. Our method significantly increases the concept coverage and outperforms existing models in various automatic evaluations. To our knowledge, we are the first to construct a CommonGen method based on global constraints. We will release our code and model later.

2 Related Work

Wang et al. (2019a) use ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019) to calculate the normalized likelihood of a sentence as the measurement of common sense, and ConceptNet is used for fine-tuning. We consider a similar fine-tuning method as proposed in Wang et al. (2019a) but use GPT-2, which we find achieving better performance in common sense judgement. Guan et al. (2020) also use ConceptNet to fine-tune GPT-2. They took fine-tuned GPT-2 as the generative model, and fine-tuning of GPT-2 on ConceptNet is to improve the long-term relevance among the sentences in generated stories. In contrast, the fine-tuned GPT-2 works as a discriminator in our method to measure the common sense of a single sentence.

Previous work has also considered enforcing global constraints with reinforcement learning for text generation. Wu et al. (2018) and Du and Ji (2019) consider automatic evaluations such as BLEU and METEOR. Yu et al. (2017) consider the naturality of the sentences measured by an adversarial discriminator. In contrast to their work, we make use of a set of different metrics to comprehensively evaluate the quality of output sentences, without the need of a reference output. Ziegler et al. (2019) consider the human evaluation of the generated sentence. We differ from the previous work in that we use a range of automatic measures to score the fluency and common sense in guided reinforcement learning.

3 Task and Model

The input of CommonGen is a set of $M$ concepts $X = \{x_1, ..., x_M\}$, where every $x_i$ indicates a noun or verb. The target output is a natural sentence containing these concepts $Y = [y_1, ..., y_N]$, where $y_i$ is a word. We expect that the output sentence is grammatical, fluent and does not violate common sense. The task is to learn a function to map the concept set $X$ to a proper sentence $Y$.

Lin et al. (2019) solve this task supervised learning. Given a training sample $[X, Y]$, the objective is

$$\ell_{mle} = - \log P(Y|X)$$

$$= - \sum_{t=1}^{N} \log P(y_t|y_{<t}, X).$$

In this paper, our generative model is UniLM (Dong et al., 2019).

4 Global Guidance

4.1 Fluency and Common Sense

Inspired by Holtzman et al. (2018); Han et al. (2020), we use perplexity on GPT-2 (Radford et al., 2019) to evaluate the fluency and common sense of the generated sentences.

Since the domain of the perplexity is $(0, \infty)$, perplexity is not a suitable value as reward. We use
We compute the weighted sum of the above for a comprehensive global score,

\[ R(X, Y) = w_1 S_{PPL}(Y) + w_2 S_{PPL,F}(Y) + w_3 S_{cov}(X, Y) + w_4 S_{len}(X, Y) \]

where \( w_1, w_2, w_3, w_4 \) are hyper-parameters. \( w_1 \) and \( w_2 \) cannot be non-zero at the same time.

\[ S_{PPL}(Y) = \begin{cases} 0, & PPL(Y) \leq L \\ \frac{U - PPL(Y)}{U - L}, & U < PPL(Y) < L \\ 1, & PPL(Y) \geq U \end{cases} \]

where “U” and “L” are the pre-defined upper and lower bounds, respectively.

As Wang et al. (2019a) shows, the performance of pre-trained language models on common sense can be improved, if the model is fine-tuned on ConceptNet (Speer et al., 2017). Thus, we fine-tune GPT-2 on ConceptNet and evaluate the ability of common sense judgement with task 4 (Wang et al., 2020) in SemEval-2020. The accuracy of GPT-2 improves from 76.23% to 83.35%. The reward of fine-tuned GPT-2 is \( S_{PPL,F}(Y) \).

4.2 Concept Coverage

For CommonGen, the generated sentence is encouraged to contain as many input concepts as possible, so we also consider the coverage of the input concepts as a global constraint. To calculate the coverage, we match the lemmas of the output words and the input concepts. The definition of concept coverage is

\[ S_{cov}(X, Y) = \frac{\text{Captured concepts}}{\text{Input concepts}} \in [0, 1] \]

4.3 Sentence Length

Intuitively, it is easier to capture more input concepts with more output words. In addition, longer sentences tend to get lower GPT-2 perplexity.

In order to penalize the generated sentences that are two times or more longer than the input, we design the following length score,

\[ S_{len}(X, Y) = \min \left( \frac{2 \cdot \text{len}_{\text{input}}}{\text{len}_{\text{output}}}, 1 \right) \in (0, 1] \]

where \( \text{len}_{\text{input}} \) and \( \text{len}_{\text{output}} \) indicate the number of input concepts and the length of the output sentence, respectively.

4.4 Comprehensive Score

We compute the weighted sum of the above for a comprehensive global score,

\[ R(X, Y) = w_1 S_{PPL}(Y) + w_2 S_{PPL,F}(Y) + w_3 S_{cov}(X, Y) + w_4 S_{len}(X, Y) \]

where \( w_1, w_2, w_3, w_4 \) are hyper-parameters. \( w_1 \) and \( w_2 \) cannot be non-zero at the same time.

We apply Pattern (Smedt and Daelemans, 2012) to obtain the lemma of a word.

5 Reinforcement Learning

We use REINFORCE algorithm (Williams, 1992). The objective function is

\[ \ell_{rl} = E_{\hat{Y} \sim P(\hat{Y}|X)} R(\hat{Y}, X) \]

where \( \hat{Y} \) is a sentence sampled based on \( X \) by the generative model, and \( R \) is reward.

The gradient can be estimated using Monte-Carlo sampling. At each step of the algorithm, we sample multiple \( \hat{Y} \) based on the generative model, calculate the reward \( R(\hat{Y}, X) \) and compute the gradient. Specifically, for each sampled pair \( (\hat{Y}, X) \), we calculate the gradient as

\[ \nabla_\theta \ell_{rl}(\hat{Y}, X) = (R(\hat{Y}, X) - \bar{R}) \nabla_\theta \log P(\hat{Y}|X) \]

where \( \theta \) is the parameter to be optimized in the generative model. In order to reduce the variance of the gradient, we subtract a baseline value \( \bar{R} \) from the reward. \( \bar{R} \) is the estimated average reward over multiple sampled sentences at every step as described by Wu et al. (2018).

Inspired by the Dagger algorithm (Ross et al., 2011), which performs better in tasks such as paraphrase generation.

By increasing the probabilities of proper sentences (Du and Ji, 2019), we sample multiple high quality sentences with beam search and calculate \( R(X, Y) \) based on these sentences, which is similar to the \( \epsilon \)-greedy algorithm (Tokin and Palm, 2011).

6 Decoding

The global guidance can also be used to improve the decoding process. We construct the guided decoding processes at three levels.

6.1 Word level: Interpolation

We use the interpolation of the distribution of generation model \( P_{gm}(y_t|y_{<t}, X) \) and GPT-2 \( P_{gpt}(y_t|y_{<t}) \) to predict the next word:

\[ P(y_t|y_{<t}, X) = \alpha P_{gm}(y_t|y_{<t}, X) + (1 - \alpha) P_{gpt}(y_t|y_{<t}) \]

where \( \alpha \) is hyper-parameter.

6.2 Fragment level: Guided Beam Search

Beam search (Freitag and Al-Onaizan, 2017) generates a sentence with the (locally) maximum likelihood. For a beam with width \( K \), in each step
We use the comprehensive score with the highest score meets the constraint of CommonGen better than the sentence with the largest likelihood. Note that, the weights $w_1$ and $w_2$ cannot be non-zero at same time. Baseline Re-rank means the weights used for guided decoding baseline model.

Specifically, we construct a guided beam $B_g$ that works in parallel with the traditional beam $B$. $B_g$ is used to save the sentence fragments with the highest comprehensive scores $R(X, Y)$ in each decoding step, which is shown in the Algorithm 1. As the perplexity cannot measure fragments properly, the comprehensive score $R(X, Y)$ only contains $S_{cov}(X, Y)$ and $S_{len}(X, Y)$. Generally, the sentence fragments capturing more concepts will be saved in the guided beam. When multiple sentences have the same concept coverage, we keep the shorter fragments.

### 6.3 Sentence Level: Re-ranking

We use the comprehensive score $R$ to re-rank the predicted candidate fragments obtained from $B$, select the $K$ fragments with the highest likelihood. Note that, the weights $w_1 \cdots w_4$ of the comprehensive score during re-ranking is different of the weights during training.

### 7 Experiments

#### 7.1 Experimental Settings

**Data** The CommonGen dataset (Lin et al., 2019) contains different concept sets and each concept set corresponds to 2-5 sentence descriptions.

|                          | $w_1$ | $w_2$ | $w_3$ | $w_4$ |
|--------------------------|-------|-------|-------|-------|
| Training                 | [0, 20] | [0, 20] | 200   | 0     |
| Guided Beam-ranking      | 0     | 0     | 2000  | 200   |
| Re-ranking               | [0, 110] | [0, 110] | 210   | 10    |
| Baseline Re-ranking      | 0     | 110   | 110   | 110   |

Table 1: Weights for comprehensive score. $w_1$, $w_2$, $w_3$, $w_4$ are weights for $S_{ppl}$, $S_{pplr}$, $S_{cov}$ and $S_{len}$, respectively. {0, 100} in table means that $w_1$ and $w_2$ cannot be non-zero at same time. Baseline Re-rank means the weights used for guided decoding baseline model.

### Hyper-parameters

We choose the pre-trained Unified Language Model (UniLM, Dong et al. (2019)) as our generative model. Following the training strategy of Lin et al. (2019), we first do supervised training based on the “unilmv1-large-cased” model. During training, the batch size is 48, the word masking probability is 0.7, the learning rate warm-up is 0.1, and the learning rate is $1e-5$. After 10 epoch of supervised training, we obtain the baseline model. Based on the baseline model, we then use our comprehensive score to perform reinforcement learning of the baseline for 1 epoch. All hyper-parameters are the same as in the supervised training, except that the learning rate is set to $1e-8$. During reinforcement learning and guided decoding, we set the beam search hyper-parameter $K = 5$. In the word level guided decoding, we set $\alpha = 0.3$ in Equation 1. The weights for the comprehensive score are shown in Table 1.

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1For the baseline model, we use the code from https://github.com/INK-USC/CommonGen.
We compare different models using three N-gram based evaluation metrics: BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and METEOR (Banerjee and Lavie, 2005). We additionally adopt CIDEr (Vedantam et al., 2015) and SPICE (Anderson et al., 2016) which are specially designed for evaluating captioning tasks, as the CommonGen dataset is constructed from video captions. Moreover, we adopt three other metrics associated with the CommonGen task: the average concept coverage rate “Cov”, the average perplexity calculated by the fine-tuned GPT-2 “PPL” and the average sentence length “Len”.

### 7.2 Main Results

We compare our approach with recent state-of-the-art approaches (i.e., “UniLM*”, “UniLM-v2†”, (Bao et al., 2020), “BART†” (Lewis et al., 2019) and “T5†” (Raffel et al., 2019)) and summarize the results in Table 2. Models listed in Table 2 with the “RL” prefix are our models with different architectures. More specifically, “RLs” represents that the sentences are randomly sampled by \( P(Y|X) \) in reinforcement learning while “RLb” represents that the sentences are sampled using beam search. We use the fine-tuned GPT-2 and original GPT-2 to calculate the perplexity score for “GPT2F” and “GPT2” respectively. The model with the subscript “gd” denotes that the output are generated by guided decoding while the model without “gd” predict a output using a traditional beam search.

In general, models with guided training and decoding processes effectively improve the generation performance in most automatic evaluation metrics. Compared with the major baseline “UniLM*”, our best-performing model “RLb+GPT2F*gd” improves the scores of ROUGE2 by 0.89, ROUGEL by 0.77, BLEU3 by 0.7, BLEU4 by 0.7, METOR by 1.6, CIDEr by 0.99, SPICE by 1.4 and concept coverage by 8.05. It demonstrates the advantage of reward-based tuning using global guidance. We also compare our results with three other models on CommonGen reported by Lin et al. (2019): UniLM-v2, BART and T5. “RLb+GPT2F*gb” achieves the state-of-the-art in CommonGen.

Comparing “RLs···” and “RLb···” with the baseline, we find that guided training and decoding with random sampling provides relatively little improvement, while beam search sampling improves the performance by a large margin. This is mainly because beam search sampling can generate high-quality samples with greater probabilities, improving the efficiency of reinforcement learning.

We also investigate the impact of fine-tuning on GPT-2 by comparing “RLb+GPT2···” and “RLb+GPT2F···”. It is observed that the models
Table 4: Results using the reward calculated by the perplexity or the coverage rate solely. “Cov” means that only the coverage score $S_{cov}$ is used as the reward in reinforcement learning, “GPT2F” means that only the perplexity $S_{PPL,F}$ is used as the reward.

Table 5: Comparison of non-module function in guided decoding method. “Beam” shows the result of “RLb+GPT2F”, and “GBeam+M+R” shows the result of “RLb+GPT2F gd”. “Beam” represents the traditional beam search. “M” represents the word level guided decoding, i.e. GPT-2 interpolation. “GBeam” represents the fragment level guided decoding (i.e. the guided beam search). “R” represents the sentence level guided beam search (i.e. re-ranking of the beam search result).

7.3 Results of Using Test Inputs to Mitigate Domain Gap

Since reinforcement learning only needs input concepts during training, we continuously train the “RLb+GPT2F” with the input concepts of the test set to mitigate the domain gap between the training and test datasets. In Table 3, we report the result of “RLb+GPT2F” with a training stage on test inputs. Note that the gold reference sentences of the test set are not used here. Comparing the result with Table 2, we can see that training with test inputs achieves a significant increase in concept coverage and SPICE score.

7.4 Human Evaluation

To assess the quality of our method more accurately, we conduct a human evaluation of generation fluency and common sense. From the examples generated by “UniLM”, “UniLM gd”, “RLb+GPT2F” and “RLb+GPT2F gd”, we randomly sample 100 generated sentences. In terms of generation fluency and common sense, 3 volunteers are asked to select the best sentences generated by these 4 models. We summarize the results in Figure 5, where each percentage is averaged different volunteers. Note that we allow ties, so the percentages do not add up to one.

Overall, our “RLb+GPT2F gd” achieves the best results on both metrics. “UniLM gd” achieves the worst results, indicating that direct use of guided decoding on the supervised model may harm performance. On the other hand, the improvement of “RLb+GPT2F gd” over “RLb+GPT2F” shows that using guided decoding is beneficial to our model trained with reinforcement learning. The discrepancy in the usefulness of guided decoding may be explained by the fact that “RLb+GPT2F gd” is trained using guided training.

7.5 Ablation

We study the functions and roles of different components of our method via the ablation experiments.

Reward in reinforcement learning We study the components in the reward function: the perplexity score and coverage score. The results are shown in Table 4.
increases the automatic evaluation and coverage scores from the baseline. On the other hand, training with fine-tuned GPT-2 does not improve the automatic evaluation significantly over the baseline, but results in lower perplexity.

Guided decoding We study the utility of the three levels of guided decoding. The results are shown in Table 5. By comparing “Beam+M” and “Beam”, we conclude that the interpolation of GPT-2 probability improves the overall quality of the generated sentences. It increases the automatic evaluation scores and reduces the perplexity. However, it results in a little drop of the concept coverage, because GPT-2 focus more on the fluency. By comparing “GBeam+M+R” with “Beam+M+R”, it is obvious that the guided beam search generally increases the sentence quality and the concept coverage. It increases the concept coverage by 2.14 and slightly improves the automatic evaluation and perplexity. Guided beam search is significantly more effective than GPT-2 interpolation, implying that the concept coverage plays an important role in global guidance. By comparing “Beam+R” and “Beam+M+R” with “Beam” and “Beam+M”, we see that the re-ranking process increases the concept coverage by nearly 4. It also improves the various automatic evaluations by 0.4~1. Re-ranking makes the most significant improvement compared with guided decoding at the word and fragment levels, because it is based on the global score of the complete sentences.

7.6 Comparison with Supervised Method

To investigate how the reinforcement learning method influences the text generation compared with supervised learning, we conduct experiments on the development dataset and summarize the results in Figure 4. Figure 4 (a) (b) and (c) show BLEU4, CIDEr and the coverage rate of different epochs. It shows that training using supervised learning (> 10 epochs) may hinder the performance. Instead of adhering to supervised training, using reinforcement learning to incorporate global guided information can generally and significantly contribute to the model on various metrics.

7.7 Concept Ordering

Typical supervised learning using the cross-entropy loss forces the model to mimic a “standard” human-written token sequence. The concept order is fixed in the human-written token sequence, which may hinder the diversity of texts generated by the trained model. We use reinforcement learning to address this limitation because reinforcement learning provides a reward that is independent of the concept order in the human-written token sequence. To empirically verify the advantage of our method in promoting flexibility, we study the concept orders in the sentences generated by the supervised learning based model (“UniLM”) and the reinforcement learning based model (“RLb+GPT2F”).
1. **INPUT CONCEPT:** {stage, perform, routine, music}
   - **RLb+GPT2Fgd:** A group of people perform a routine on the stage during the music. (48.25)
   - **UniLM:** A group of people perform a routine at the music festival. (74.17)

2. **INPUT CONCEPT:** {snap, smile, finger, sit}
   - **RLb+GPT2Fgd:** A man sits on a bench and snaps a finger at a smiling woman. (45.32)
   - **UniLM:** Someone sits next to someone and snaps a finger at him. (77.18)

3. **INPUT CONCEPT:** {dog, stand, groom, table}
   - **RLb+GPT2Fgd:** A man is grooming a dog and standing next to a table. (35.16)
   - **UniLM:** A man is grooming a dog and grooming it on a table. (85.56)

4. **INPUT CONCEPT:** {throw, ball, pitcher, batter}
   - **RLb+GPT2Fgd:** A pitcher throws a ball to a batter. (11.88)
   - **UniLM:** A batter throws a ball to the pitcher. (38.54)

|          | Train | Dev |
|----------|-------|-----|
| UniLM    | 0.23  | 0.553 |
| RLb+GPT2Fgd | 0.239 | 0.517 |

Table 6: Case study of an generated sentences from the baseline model “UniLM” and “RLb+GPT2Fgd”. Value in the bracket is the perplexity of fine-tuned GPT-2.

Figure 6: Minimum edit distance of concepts order between ground truth and generated sentences. Blue bars show the minimum edit distances on training and development dataset between the ground truth and sentences generated by “UniLM”. Orange bars show results for “RLb+GPT2Fgd”. Learning based model (“RLb+GPT2Fgd”). For each input, we calculate the minimum edit distance between the ordered concept lists drawn respectively from the reference sentence and the generated sentence to measure their difference. We compare the average minimum edit distance of “UniLM” and “RLb+GPT2Fgd” on both the training dataset and the development dataset in Figure 6. The larger minimum edit distance of “RLb+GPT2Fgd” in Figure 6 suggests that our method provides more freedom in concept ordering and hence may generate more diversified sentences.

8 **Case Study**

We provide a case study in Table 6. Given the input concepts, we show the sentence generated by the baseline model “UniLM” and our best model “RLb+GPT2Fgd”. For the first three cases, the sentences generated by “RLb+GPT2Fgd” contain more input concepts than the baseline model, and the coverage rates are 1. In the first case, our model reasonably included the concept of “stage” in the sentence without undermining the fluency. In the second case, our model not only captures the concept of “smile”, but also solves the problem of ambiguous reference of the sentence by the baseline model. In the third case, compared with the baseline model, our output not only captures “stand”, but also avoids the repetition of “grooming”, which seems to be an improvement in general. In the last case, the sentences generated by the two models are both grammatically correct. But from human’s common sense, pitchers are more likely to throw the ball than batters. Therefore, our generated sentences are more in line with common sense. Furthermore, according to the perplexity comparison provided in Table 6, it can be observed that the fine-tuned GPT-2 has the ability to measure the fluency and common sense of the generated sentence.

9 **Conclusion**

We used CommonGen as a case for investigating constrained text generation. A comprehensive score for the sentence measured fluency, common sense, and concept coverage and served as the global guidance of the generative model. We took the comprehensive score as the reward and use reinforcement learning to train the model. We also designed a guided decoding method at word, fragment and sentence levels. Our experiments demonstrated that our method significantly increases the concept coverage compared with the baseline model, and generally improved the scores of various automatic evaluation and human evaluation.
References

Peter Anderson, Basura Fernando, Mark Johnson, and Stephen Gould. 2016. **SPICE: semantic propositional image caption evaluation.** In Computer Vision - ECCV 2016 - 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings. Part V, volume 9909 of Lecture Notes in Computer Science, pages 382–398. Springer.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Satanjeev Banerjee and Alon Lavie. 2005. **METEOR: an automatic metric for MT evaluation with improved correlation with human judgments.** In Proceedings of the Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization@ACL 2005, Ann Arbor, Michigan, USA, June 29, 2005, pages 65–72.

Hangbo Bao, Li Dong, Furu Wei, Wenhui Wang, Nan Yang, Xiaodong Liu, Yu Wang, Songhao Piao, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2020. **Unilmv2: Pseudo-masked language models for unifield language model pre-training.** CoRR, abs/2002.12804.

Marco Damonte and Shay B. Cohen. 2019. **Structural neural encoders for amr-to-text generation.** In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 3649–3658.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. **BERT: pre-training of deep bidirectional transformers for language understanding.** In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers), pages 4171–4186. Association for Computational Linguistics.

Li Dong, Nan Yang, Wenhui Wang, Furu Wei, Xiaodong Liu, Yu Wang, Jianfeng Gao, Ming Zhou, and Hsiao-Wuen Hon. 2019. Unified language model pre-training for natural language understanding and generation. In Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, 8-14 December 2019, Vancouver, BC, Canada, pages 13042–13054.

Wanyu Du and Yangfeng Ji. 2019. **An empirical comparison on imitation learning and reinforcement learning for paraphrase generation.** In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019, Hong Kong, China, November 3-7, 2019, pages 6011–6017. Association for Computational Linguistics.

Xiaocheng Feng, Ming Liu, Jiahao Liu, Bing Qin, Yibo Sun, and Ting Liu. 2018. **Topic-to-essay generation with neural networks.** In Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, IJCAI 2018, July 13-19, 2018, Stockholm, Sweden, pages 4078–4084. ijcai.org.

Markus Freitag and Yaser Al-Onaizan. 2017. **Beam search strategies for neural machine translation.** In Proceedings of the First Workshop on Neural Machine Translation, NMT@ACL 2017, Vancouver, Canada, August 4, 2017, pages 56–60. Association for Computational Linguistics.

Albert Gatt and Emiel Krahmer. 2018. **Survey of the state of the art in natural language generation: Core tasks, applications and evaluation.** J. Artif. Intell. Res., 61:65–170.

Jian Guan, Fei Huang, Minlie Huang, Zhihao Zhao, and Xiaoyan Zhu. 2020. A knowledge-enhanced pretraining model for commonsense story generation. Trans. Assoc. Comput. Linguistics, 8:93–108.

Wenjuan Han, Liwen Zhang, Yong Jiang, and Kewei Tu. 2020. Adversarial attack and defense of structured prediction models. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 2327–2338. Online. Association for Computational Linguistics.

Ari Holtzman, Jan Buys, Maxwell Forbes, Antoine Bosselut, David Golub, and Yejin Choi. 2018. Learning to write with cooperative discriminators. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers, pages 1638–1649. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2019. **BART: denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension.** CoRR, abs/1910.13461.

Bill Yuchen Lin, Ming Shen, Yu Xing, Pei Zhou, and Xiang Ren. 2019. **Commongen: A constrained text generation dataset towards generative commonsense reasoning.** CoRR, abs/1911.03705.

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.
Yang Liu and Mirella Lapata. 2019. Text summarization with pretrained encoders. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 3730–3740, Hong Kong, China. Association for Computational Linguistics.

Manuel Mager, Ramón Fernández Astudillo, Tahira Naseem, Md. Arafat Sultan, Young-Suk Lee, Radu Florian, and Salim Roukos. 2020. Gpt-too: A language-model-first approach for amr-to-text generation. CoRR, abs/2005.09123.

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.

Matthew E. Peters, Mark Neumann, Mohit Iyyer, Matt Gardner, Christopher Clark, Kenton Lee, and Luke Zettlemoyer. 2018. Deep contextualized word representations. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2018, New Orleans, Louisiana, USA, June 1-6, 2018, Volume 1 (Long Papers), pages 2227–2237. Association for Computational Linguistics.

Ratish Puduppully, Li Dong, and Mirella Lapata. 2019. Data-to-text generation with content selection and planning. In The Thirty-Third AAAI Conference on Artificial Intelligence, AAAI 2019, The Thirty-First Innovative Applications of Artificial Intelligence Conference, IAAI 2019, The Ninth AAAI Symposium on Educational Advances in Artificial Intelligence, EAAI 2019, Honolulu, Hawaii, USA, January 27 - February 1, 2019., pages 6908–6915.

Alec Radford, Jeffrey Wu, Rewon Child, David LAN, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI Blog, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. CoRR, abs/1910.10683.

Ehud Reiter and Robert Dale. 2000. Building natural language generation systems. Cambridge university press.

Stéphane Ross, Geoffrey J. Gordon, and Drew Bagnell. 2011. A reduction of imitation learning and structured prediction to no-regret online learning. In Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, AISTATS 2011, Fort Lauderdale, USA, April 11-13, 2011, volume 15 of JMLR Proceedings, pages 627–635. JMLR.org.

Tianxiao Shen, Tao Lei, Regina Barzilay, and Tommi S. Jaakkola. 2017. Style transfer from non-parallel text by cross-alignment. In Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, 4-9 December 2017, Long Beach, CA, USA, pages 6830–6841.

Tom De Smedt and Walter Daelemans. 2012. Pattern for python. J. Mach. Learn. Res., 13:2063–2067.

Lin Feng Song, Ante Wang, Jinsong Su, Yue Zhang, Kun Xu, Yubin Ge, and Dong Yu. 2020. Structural information preserving for graph-to-text generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7987–7998, Online. Association for Computational Linguistics.

Lin Feng Song, Yue Zhang, Zhiguo Wang, and Daniel Gildea. 2018. A graph-to-sequence model for amr-to-text generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics, ACL 2018, Melbourne, Australia, July 15-20, 2018, Volume 1: Long Papers, pages 1616–1626.

Robyn Speer, Joshua Chin, and Catherine Havasi. 2017. Conceptnet 5.5: An open multilingual graph of general knowledge. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA, pages 4444–4451. AAAI Press.

Nisan Stiennon, Long Ouyang, Jeffrey Wu, Daniel Ziegler, Ryan Lowe, Chelsea Voss, Alec Radford, Dario Amodei, and Paul F Christiano. 2020. Learning to summarize with human feedback. In Advances in Neural Information Processing Systems, 33.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. In Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada, pages 3104–3112.

Jiwei Tan, Xiaojun Wan, and Jianguo Xiao. 2017. Abstractive document summarization with a graph-based attentional neural model. In Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1171–1181.

Michel Tokic and Günther Palm. 2011. Value-difference based exploration: Adaptive control between epsilon-greedy and softmax. In KI 2011: Advances in Artificial Intelligence, 34th Annual German Conference on AI, Berlin, Germany, October 4-7, 2011. Proceedings, volume 7006 of Lecture Notes in Computer Science, pages 335–346. Springer.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all
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.

Cunxiang Wang, Shuailong Liang, Yili Jin, Yilong Wang, Xiaodan Zhu, and Yue Zhang. 2020. SemEval-2020 task 4: Commonsense validation and explanation. In Proceedings of The 14th International Workshop on Semantic Evaluation. Association for Computational Linguistics.

Cunxiang Wang, Shuailong Liang, Yue Zhang, Xiaonian Li, and Tian Gao. 2019a. Does it make sense? and why? A pilot study for sense making and explanation. In Proceedings of the 57th Conference of the Association for Computational Linguistics, ACL 2019, Florence, Italy, July 28- August 2, 2019, Volume 1: Long Papers, pages 4020–4026. Association for Computational Linguistics.

Wenlin Wang, Zhe Gan, Hongteng Xu, Ruiyi Zhang, Guoyin Wang, Dinghan Shen, Changyou Chen, and Lawrence Carin. 2019b. Topic-guided variational autoencoders for text generation. CoRR, abs/1903.07137.

Ronald J. Williams. 1992. Simple statistical gradient-following algorithms for connectionist reinforcement learning. Mach. Learn., 8:229–256.

Lijun Wu, Fei Tian, Tao Qin, Jianhuang Lai, and Tie-Yan Liu. 2018. A study of reinforcement learning for neural machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, Brussels, Belgium, October 31 - November 4, 2018, pages 3612–3621. Association for Computational Linguistics.

Lantao Yu, Weinan Zhang, Jun Wang, and Yong Yu. 2017. Sequgan: Sequence generative adversarial nets with policy gradient. In Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence, February 4-9, 2017, San Francisco, California, USA, pages 2852–2858. AAAI Press.

Daniel M. Ziegler, Nisan Stiennon, Jeffrey Wu, Tom B. Brown, Alec Radford, Dario Amodei, Paul Christiano, and Geoffrey Irving. 2019. Fine-tuning language models from human preferences. CoRR, abs/1909.08593.