Fine-Grained Controllable Text Generation Using Non-Residual Prompting

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Abstract

The introduction of immensely large causal language models (CLMs) has rejuvenated the interest in open-ended text generation. However, controlling the generative process for these Transformer-based models is at large an unsolved problem. Earlier work has explored either plug-and-play decoding strategies or more powerful but blunt approaches such as prompting. There hence currently exists a trade-off between fine-grained control and the capability for more expressive high-level instructions. To alleviate this trade-off, we propose an encoder-decoder architecture that enables intermediate text prompts at arbitrary time steps. We propose a resource-efficient method for converting a pre-trained CLM into this architecture and demonstrate its potential in various experiments, including the novel task of contextualized word inclusion. Our method provides strong results in multiple experimental settings, proving itself to be both expressive and versatile.[1]

1 Introduction

A causal language model (CLM) is a language model trained using a simple next-token prediction objective. Current CLMs are typically based on the Transformer architecture (Vaswani et al., 2017), which has resulted in unprecedented text generation capabilities (Radford et al., 2018a,b; Brown et al., 2020). Even so, the generation process of a CLM is difficult to control, as one is forced to gradually decode the next-step prediction one token at a time. This inhibits the applicability of CLMs when one intends for the generated text to fulfill certain criteria, and not only be a linguistically sound continuation in a given context.

Being able to control the text generation process is crucial for many real-world applications. As a straightforward example, we may want to control the generated text to counter the many biases that modern CLMs have been shown to possess (Bordia and Bowman, 2019). However, most applications require a greater degree of control, as one often wishes to steer the text generation in a specific direction, such as generating a story to a given plot (Li et al., 2013; Yao et al., 2019; Riedl, 2021), or sticking to a certain topic (Keskar et al., 2019). Some areas require stringent and fine-grained control, as the many data-to-text tasks (Gardent et al., 2017; Leppänen et al., 2017; Koncel-Kedziorski et al., 2019), which necessitates that the generated text mediates very specific information and facts.

Due to this apparent need for controllable text generation, recent work (see Section 2.1) has explored different methods to steer and constrain the generation process of a CLM. There are mainly two lines of research in this area. The more traditional approach focuses on fine-grained control and how to steer the generation process at arbitrary points, while still adhering to the current context. This is often achieved by independently modifying the predicted vocabulary distribution at each decoding step. However, this decouples the CLM from the control method, prohibiting the CLM's ability to plan accordingly and thus severely limits the type of control that can be formulated.

The second approach instead opts for more expressive and high-level control, letting the CLM itself interpret and incorporate the instruction into the text generation. This is often done via either a fine-tuning objective or, as is currently common, by formulating the instruction as a textual context (referred to as prompting). Although expressive, these approaches are less effective than the previous ones in controlling generation at specific points. This is due to the prompt's influence being negatively correlated with the distance from the prompt to the next predicted token (Zou et al., 2021), making prompting difficult for non-adjacent text.

[1] Code and models: https://Github.com/FreddeFrallan/Non-Residual-Prompting

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In an attempt to bridge the gap between fine-grained control and the expressiveness of prompts, we propose an architecture that permits long-distance and independent prompting throughout the generation process. This architecture has an encoder-decoder setup, where the encoder influences the decoder via a novel non-residual attention schema. Along with theoretical arguments for the benefits of this architecture, we provide a resource-efficient self-supervised method for converting a pre-trained CLM into this setup.

In addition to evaluating on the original CommonGen dataset (Lin et al., 2020), we propose a new contextualized version of CommonGen, called Contextualized CommonGen ($\mathrm{C^2G}$EN) and evaluate relevant methods on it. This new dataset extends the task to generating a sentence which includes a given set of words, while simultaneously adhering to a given context. We find that no previous solution is capable of handling this task, either barely including 50% of the target words, or not generating text of satisfactory quality.

Our Contributions: (1) An encoder-decoder architecture based on a novel attention module which enables prompting at arbitrary time steps. (2) A resource-efficient method, which requires no labeled data, for converting a pre-trained CLM into this architecture. (3) The introduction of the contextualized word inclusion task, through the $\mathrm{C^2G}$EN dataset. (4) Extensive testing of related baselines and our proposed method, via both automatic and human evaluation.

2 Related Work

2.1 Controllable Text Generation

This section briefly introduces the related work for constrained text generation. A detailed description of each method, their strengths and weaknesses, and how they are configured to form our baselines is available in Appendix D.

Decoding strategies operate directly on the CLM's predicted vocabulary distribution at each time step, and are hence often model-agnostic. Dathathri et al. (2020) propose Plug-and-Play-Language-Models (PPLM), which adjust the distribution in accordance with the gradients of an external discriminator model. Pascual et al. (2021) introduce Keyword2Text, which steers the CLM to include target words by directly increasing their sampling probability, along with their GloVe (Pennington et al., 2014) neighbours.

Training objectives can be set up to grant generative control, such as CTRL (Keskar et al., 2019), which incorporates control codes for textual genre. KG-BART (Liu et al., 2021) utilizes a common sense knowledge graph and fine-tunes BART (Lewis et al., 2020) towards word inclusion. GDC (Khalifa et al., 2021) fine-tunes towards arbitrary discriminator signals using Reinforcement Learning. POINTER (Zhang et al., 2020) tackles word inclusion with a non-autoregressive approach, injecting words around the target words until a sentence is formed. Tailor (Ross et al., 2021) fine-tunes a T5 (Raffel et al., 2020) for fine-grained semantically-controlled text generation, with a focus on perturbing text for data augmentation.

Prompting acts within the framework of the CLM's pre-training task, as constraints are expressed through natural language. This approach was popularized by the GPT models (Radford et al., 2018b; Brown et al., 2020) and has been shown to work for many different types of constraints (Reif et al., 2021; Clive et al., 2021).

2.2 Evaluation of Generated Text

There is no standardized evaluation methodology for open-ended text generation (Howcroft et al., 2020). The large number of possible good texts hinders the usage of automatic text-overlap metrics (Papineni et al., 2002; Lin, 2004). And many human evaluations are to vague to be properly reproducible (Belz et al., 2020).

To remedy this, van der Lee et al. (2019) propose guidelines for human studies, and Gehrmann et al. (2021) argue that textual quality cannot be described through a single metric. Informed by these arguments, we report relevant metrics for various situations, without necessarily claiming one method to be superior in all aspects.

3 Model Architecture

We propose to steer a CLM's generative direction by introducing a separate "encoder" for prompt instructions, which we refer to as the *prompt model*. The prompt model interprets textual prompts and produces positional invariant key-values, which the CLM can attend to via the novel *non-residual* attention schema (Section 3.1). The positional invariance ensures that the instruction is equally applicable at any time step, and is achieved by an additional shift of its key-values (Section 3.2).

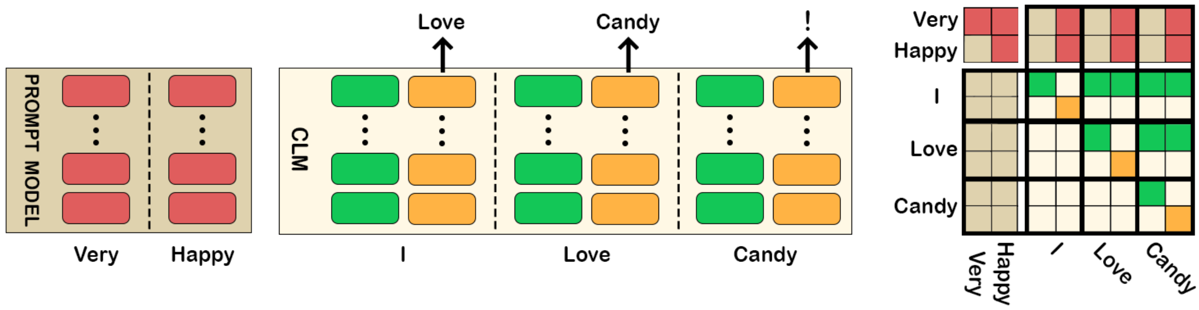

Figure 1: Illustration of the non-residual attention during multiple time steps. The textual hidden states are shown in green, the non-residual statesin yellow, and the prompt model's states in red. During the first time step both CLM streams self-attend to the input word *I*, but the non-residual stream also attends to the prompt model's hidden states for the instruction *Very Happy*. At the second time step, *Love* is input and both streams attend to the previous textual hidden states, and the non-residual stream again also attends to the prompt model's instruction.

3.1 Non-Residual Attention

To allow independent prompts at different time steps we compute two distinct streams of information for the CLM. We refer to these as the *textual* and *non-residual* streams. The **textual stream** ignores the prompt model completely, and is identical to the normal self-attention of the CLM. The **non-residual stream** is responsible for the prediction at each time step, and instead attends to both the previous steps of the textual stream, and key-values from the prompt model. This is depicted in Figure 1 and formalized in Equation 1.

Concretely, at time-step n the textual stream self-attends to the current time step and the previous textual key-values $KV_T^{i<n}$. The non-residual stream self-attends to the current time step, the previous textual key-values $KV_T^{i<n}$, and the prompt model's key-values KV_P. Finally, the next step prediction $P(w_{n+1})$ is computed from the non-residual stream.

Applying the prompt S_P to every time step in the text $S_{\text{CLM}} = \{w_1, w_2, ..., w_n\}$ thus results in:

$$\begin{aligned} KV_P &= \text{PromptModel}(S_P) \\ KV_T^n &= \text{CLM}(w_n \mid KV_T^{i<n}) \\ P(w_{n+1}) &= \text{CLM}(w_n \mid KV_p,\ KV_T^{i<n}) \end{aligned} \tag{1}$$

Non-residual key-values are hence never attended to by either streams from subsequent time steps. A prompt instruction at time step n can therefore only influence future decoding steps via the sampled token at time step n, and not through its key-values. This non-residual property of each prompt assures that the hidden state of the CLM does not deteriorate over time. Appendix C.1 further motivates this with an example.

Intuitively, this ensures that the residual key-values are only affected by textual input, allowing the CLM to operate within the limits of its pretraining objective. Furthermore, this means that one can apply different prompts at different time steps, without them disrupting each other through the CLM's internal state.[2] Further intuition on non-residual attention is available in Appendix C.

3.2 Position Invariant Transformation

Ideally, prompt instructions should be equally applicable at any time step in the generation process. However, the positional encoding system of Transformers makes this difficult, particularly absolute positional encodings (Vaswani et al., 2017). Overcoming this requires a significant amount of training of the prompt model (See Appendix C.2).

To alleviate the computational burden, we propose an architectural add-on where positional invariance is achieved by an additional set of weights, trained after the prompt model is trained on single sentence data. This reduces the overall training time, and allows one to easily fine-tune the prompt model on tasks lacking context, and apply the positional invariant transformation afterwards. This is depicted as step 3 an 4 in Figure 2.

The prompt model, being a CLM, uses causal self-attention to process text and generate L sets of key-values per time step, where L refers to the number of layers in the model. We refer to the L key-values at a time step i as kv^i. Hence, when the prompt model computes a prompt of length n, it yields the sequence of key-values $KV_P^* = \{kv^1,\ kv^2,\ ...,\ kv^n\}$.

[2]Ultimately, different prompts can be applied at each decoding step, but we imagine most use-cases will apply instructions on the sentence or paragraph level.

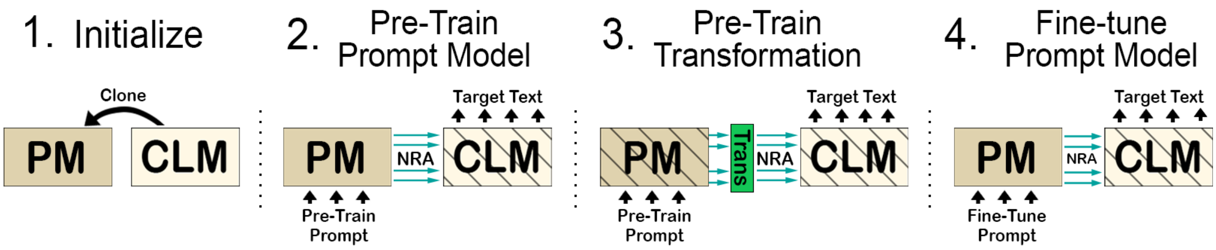

Figure 2: Overview of the resource-efficient training procedure for creating a non-residual prompt model from a pre-trained CLM. Dashed lines indicate frozen weights. Hence, the weights of the CLM are frozen throughout all training steps and the prompt model's weights are frozen in step 3. During inference, the transformation learned in step 3 is inserted again.

The positional invariant transformation, referred to as C, consists of one parameter for each of the CLMs key-value parameters.[3] The same transformation C is then applied by point-wise addition to the prompt model's output at all time steps, thus yielding the shifted key-values $KV_P = \{kv^1 + C,\ kv^2 + C,\ ...,\ kv^n + C\}$.

4 Training Procedure

Given a pre-trained CLM, we propose to train an accompanying prompt model via four distinct phases,[4] as demonstrated in Figure 2. This includes an initialization phase, two pre-training phases, and one optional fine-tuning phase. The weights of the CLM are never updated in any of the training phases.

As popularized by Raffel et al. (2020), all training, independent of task, is formulated within the framework of teacher-forced causal language modeling (Williams and Zipser, 1989). The goal is to maximize the likelihood of generating text S given prompt P, in accordance with Equation 1.

4.1 Initialization

Prior to any training, the prompt model is created by cloning the pre-trained CLM into a separate new model. The CLM and prompt models hence start with an identical set of weights. This results in an efficient starting point, since the CLM is trained to communicate with itself via self-attention, and thus also the CLM and prompt model.

[3]The size of C hence depends on the model's number of layers, number of heads and its hidden size.

[4]This does not include the pre-training of the original CLM model.

4.2 Pre-training

Pre-training is divided into two distinct phases, both relying on the text generation task of word inclusion with a target sentence length. In the first phase, the prompt model is trained to influence the CLM using only single sentence data, without any position invariant transformation. In the second phase only the position invariant transformation is learnt, by training on data with longer context. This is illustrated in Figure 3.

For both phases, training data is generated by sampling $[A, B]$ unique target words for each sentence $S = \{w_1, w_2, ..., w_n\}$, and incorporating them and the sentence length n into prompt P. The second phase utilizes sequences of multiple sentences, where each sentence is given its own prompt. During this phase, each prompt is computed independently, and the CLM attends only to the relevant prompt for each sentence.

Details regarding the corpus and sampling schema used in our experiments are available in Appendix A, and details regarding our randomized prompt template is available in Appendix A.3.

4.3 Fine-tuning

Finally, one can optionally fine-tune the prompt model towards another task or dataset. This is done by temporarily removing the positional invariant transformation, and tuning only the prompt model. The positional invariant transformation is then re-inserted afterwards, shifting the now fine-tuned prompt model's key-values.

This fine-tuning schema circumvents the problem that many NLP tasks and labeled datasets are formulated without any accompanying context. One can therefore utilize single sentence datasets, and still apply the prompt model at arbitrary time steps.

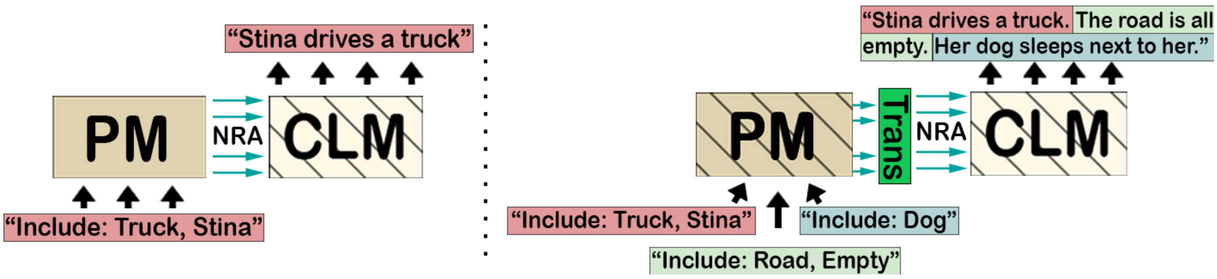

Figure 3: Detailed illustration of the two pre-training phases (Step 2 and 3 in Figure 2). Color indicates which prompt each generation step is affected by.

5 Contextualized CommonGen Dataset (C^2GEN)

CommonGen (Lin et al., 2020) is a dataset for the constrained text generation task of word inclusion. The objective of the task is to generate text that includes a given set of target words and adhering to common sense. Each sample includes 3-5 target words, taken from various image-caption datasets.

The samples in CommonGen are however all formulated without any accompanying context. We argue that this task formulation is too narrow, and that it needlessly incentivizes researchers to focus on methods that do not support context. This is orthogonal to our belief that many application areas necessitates the consideration of surrounding context. Therefore, to complement CommonGen, we provide an extended test set where an additional context is provided for each set of target words. The task is therefore reformulated to both generate commonsensical text which includes the given words, and also have the generated text adhere to the given context.

Each context is formulated as three sentences, created by human annotators from Mechanical Turk (`www.mturk.com`), as exemplified in Table 1. The annotators were tasked to create three sentences, so that a subsequent sentence would be likely to include the target words. Details regarding the creation process of C^2GEN, and its statistical properties are available in Appendix F.

Jane was excited when the teacher announced it was career week. Jane signed her dad up to visit the classroom. On the appointed day, Jane's dad showed up dressed in his work gear.

Table 1: Example context from C^2GEN, where the target words for the subsequent sentence are: **duty**, **fireman**, **firetruck**, **front** and **talk**.

6 Word Inclusion Experiments

We separate word inclusion into two different settings. In the first, the model is tasked to generate exactly 32 tokens. Requiring the model to both satisfy the word inclusion objective, and continue generating contextually relevant text. This allows methods that do not grant sentence level control to participate, such as PPLM and Keyword2Text.

In the second setting, the model is only tasked to create a single sentence, elevating the requirement of continued text generation. This setting is suitable for methods specifically trained towards creating a single common sense sentence, such as KG-BART and POINTER.

For both of these settings, we run experiments on both CommonGen and C^2GEN. Since experiments on the contextualized C^2GEN require the model to adhere to a context regardless of whether the objective is to generate a single sentence or a free text, KG-BART and POINTER are excluded from these experiments all together.

6.1 Model Configurations

Using our proposed method we train a non-residual prompt model to accompany a pre-trained GPT-2 Large model. This setup is referred to as NRP during experiments, and training details can be found in Appendix A. In order to demonstrate how more sophisticated decoding strategies can be incorporated, we also combine NRP with a slightly modified version of Keyword2Text. Details for this incorporation can be found in Appendix B.3.

The inference utilizes a beam size of 4, and any additional parameters were set according to a held-out validation set (See Appendix B). All baseline implementations are taken from their respective code repositories, and if possible the official pre-trained model (See Appendix D).

	Free Text (32 Tokens)				Single Sentence				
	Cov ↑	Ppl ↓	Self-Bleu ↓	Sense ↑	Cov ↑	Ppl ↓	Self-Bleu ↓	Sense ↑	Len
GPT-2 Large + Prompt	72.2	15.7	56.5	68.5	70.9	47.8	48.3	68.1	13.6
PPLM	13.3	17.2	21.6	**77.9**					
Keyword2Text	84.5	32.9	**13.9**	49.0					
POINTER					**98.0**	51.9	**27.7**	48.6	27.2
KG-BART					97.2	37.0	33.0	**82.4**	15.3
Our Contributions									
NRP	98.4	14.1	36.1	69.3	93.0	**24.0**	28.4	72.3	20.3
NRP + Keyword2Text	**99.5**	**14.0**	40.4	68.2	95.1	**24.0**	29.0	71.8	20.5

Table 2: Results for the Word Inclusion experiments on CommonGen.

	Free Text (32 Tokens)					Single Sentence					
	Cov ↑	Ppl ↓	Self-Bleu ↓	Sense ↑	Ctx ↑	Cov ↑	Ppl ↓	Self-Bleu ↓	Sense ↑	Ctx ↑	Len
GPT-2 Large + Prompt	57.0	12.5	31.7	**81.2**	76	56.6	24.9	31.7	**88.0**	74.3	13.6
PPLM	19.1	12.5	**15.2**	70.8	75.9						
Keyword2Text	93.9	18.0	15.4	56.5	76.4						
Our Contributions											
NRP	96.9	10.0	31.3	69.3	75.8	81.0	12.3	**22.5**	81.1	81.2	15.5
NRP + Keyword2Text	**98.6**	**9.5**	32.1	71.0	**76.8**	**82.1**	**12.5**	22.9	80.1	**82.7**	15.5

Table 3: Results for the Word Inclusion experiments on the C^{2}GEN dataset.

6.2 Evaluation Metrics

In accordance with the guidelines described in Section 2.2, we provide both quantitative and qualitative evaluation. The qualitative examples in Table 4 are intended to convey the overall style for each algorithm, and more qualitative examples are available in Appendix G.

Quantitative metrics are easily comparable, but may be less suited to convey the overall style. Our quantitative metrics are described in detail in Appendix E, and briefly below:

Word Inclusion Coverage (Cov): The percentage of target words that are included in the generated text. Both target and generated words are lemmatized, alleviating the need to match the exact form of the target word.

Perplexity (Ppl): The mean perplexity of the generated text calculated with GPT-2 XL. Although lower perplexity often indicates better language fluency, degenerate repetitions tend to result in low perplexity as well. Therefore, one should not rely on perplexity alone, but in combination with other metrics and qualitative analysis. Nevertheless, it is a metric that yields a hint of language fluency that does not require human evaluation. In the presence of contexts, as is the case with C^{2}GEN, the perplexity is conditioned on the context and typically results in significantly lower perplexity values.

Self-BLEU-5 (Self-Bleu): Average BLEU-5 overlap between all generated texts. A lower score is desired as this indicates syntactic diversity.

Common Sense (Sense): The average score on how well the generated text adheres to common sense, according to human evaluators.

Contextual Relevancy (Ctx): The average score on how well the generated text fits the given context, according to human evaluators. For more information about the human evaluation process, see Appendix E.3.

6.3 Quantitative Results

We wish to highlight that NRP, Keyword2Text, and the prompted GPT-2 all control the same underlying CLM model. Differences between these approaches are hence a result of the method, not the model. Unfortunately, all quantitative metrics (including human metrics) are intrinsically correlated with sentence length, making comparisons of single sentences non-trivial (See Appendix E).

First, we note that it is only the NRP approaches, and arguably GPT-2, that supports all four experiments. In general we find that the incorporation of Keyword2Text with NRP increases the coverage slightly, but at the cost of a slightly higher self-Bleu. Hence, for brevity, we refer to both of them as NRP throughout the remainder of this section.

NRP
The **scooter riders wear** a **T-shirt** that says "I **Ride**" on the back.
The **player presses** a **button** on the **scanner** to **place** the **card** in his or her inventory.
KG-BART
A man is **riding** a **scooter** and **wearing** a **shirt**.
A woman **presses** a **button** on a **scanner** and **places** a **card** on the **scanner**.
POINTER
you can **ride**: the **scooter**, a t t **shirt**, and then you have to **wear** a jacket.
by **pressing** a **button**, or **pressing** a **card**, the reader will **place** a **button**, and then **press** of the **card** into a **scanner** screen.

Table 4: Two independently generated sentences for NRP, KG-BART, and POINTER. The target words for the first sentence are **ride**, **scooter**, **shirt**, **wear**, and the target words for the second sentence are **press**, **card**, **place**, **button**, **scanner**.

In the CommonGen *Free Text* setting (Table 2), NRP achieves the best coverage rate by a large margin, and also the best perplexity. Noticeably, NRP outperform GPT-2 in all metrics, besides common sense where they are virtually equal. Interestingly, GPT-2's coverage is virtually the same as its free text counterpart, indicating that it quickly forgets the intended instruction. Keyword2Text generates the lowest self-Bleu, but has both the worst perplexity and common sense score. PPLM performs the best on common sense but instead fails the task completely, as demonstrated by its poor coverage.

In the CommonGen *Single Sentence* setting (Table 2), NRP fall slightly behind the specialized sentence methods in terms of coverage, but has a noticeably higher coverage than GPT-2. POINTER has the best coverage and self-Bleu, but also the worst common sense and dramatically worst perplexity. KG-BART has as expected the best common sense score, while staying fairly balanced on all other metrics. Again, NRP and GPT-2 show similar common sense scores.

For C^{2}GEN *Free Text* (Table 3), NRP performs the best on coverage and perplexity. All methods perform nearly identical on the context score. Both PPLM and Keyword2Text perform better than they did on CommonGen, but Keyword2Text is still worst on perplexity and common sense, and PPLM still performs the worst on coverage. As expected, GPT-2 performs poorly on contextualized word inclusion, demonstrated by its low coverage. This indicates that GPT-2 acts more as a regular CLM, ignoring the instruction prompt, which explains its high common sense score.

Finally, NRP performs significantly better on coverage, perplexity, self-Bleu and context with *Single Sentences* on C^{2}GEN (Table 3). GPT-2 performs better on common sense, which is likely due to it focusing less on the word inclusion objective. Again, GPT-2 achieves a similar coverage as its *Free Text* counterpart.

6.4 Qualitative Results

As demonstrated in Table 4, NRP and GPT-2 tend to generate more linguistically complicated sentences, with more flow, compared to that of KG-BART. While stylistic complexity is arguably something desirable, it has the drawback that it increases the chance of generating text that breaks common sense. Our inspection also confirms that POINTER generates long sentences with weird formulations, that often break common sense and being syntactically incorrect.

Examples of generated texts from all methods are available in Appendix G. Keyword2Text often inserts multiple line breaks, and sometimes gets stuck repeating a word. The differences between NRP, PPLM and GPT-2 are more subtle, the major distinction being that PPLM comes off as slightly more fluid in its formulations.

7 Sentence Length Experiments

The inclusion of sentence length in the pre-training objective (Section 4.2), gives an additional level of generative control over the linguistic style. As demonstrated in Table 5, the model incorporates and plans using the prompted sentence length, and changes the wording and content accordingly.

L_P	L_G	Target Words	Generated Sentence
6	6	drink, sit, table, wine	The **wine-drinkers sit** on the **table**.
12	11	drink, sit, table, wine	The guests **sit** at a **table** and **drink wine** or beer.
18	16	drink, sit, table, wine	The guests **sit** at a **table** and **drink wine**, while the hostess sits on the floor.
8	8	amazing, trump, politics, victory	The **Trump victory** was an **amazing** victory in **politics**.
14	14	amazing, trump, politics, victory	The **Trump victory** was an "**amazing**" and "incredible" victory for American **politics**, he said.
20	25	amazing, trump, politics, victory	The **Trump victory** in the 2016 presidential election was an **amazing** victory for American **politics** as a whole, but it wasn't just about Donald J.

Table 5: Examples of generated sentences for different prompted sentence lengths, using the pre-trained word inclusion model. L_p is the prompted length and L_G shows the resulting generation length.

We note that the model tends to prioritize textual quality over strictly sticking to the exact number of words. To measure this discrepancy, we generate sentences for all CommonGen validation samples for different prompted sentence lengths. Figure 4 shows the results from this experiment, displaying the expected offset for different prompted sentence lengths.

The mean offset is always above 0 and below 1, meaning the CLM can be expected to generate a slightly longer sentence than intended. The standard deviation increases both as the prompted length approaches long, and short sentences. This matches the sentence distribution of the pre-training dataset, as demonstrated in Table 6 found in Appendix A.

8 Discussion and Future Work

We opted to demonstrate our architecture's capabilities on the task of word inclusion, since quantitative comparisons on this task are relatively straight-forward, compared to most other open-ended text generation tasks. While experimental results indicate the versatility of our approach, it is important to note that the method conceptually generalizes to a much wider range of tasks.

Our non-residual architecture enables the use of prompt instructions at arbitrary time steps, but is not limited to word inclusion. We hence encourage future work to pursue the incorporation of multi-task prompt learning, as being able to apply flexible prompts with precision would be a big step forward in the many areas striving to use CLMs. Indeed, we consider the ability to control the text generation process while considering context crucial for any tool intended for human editors.

Admittedly, our training method for realizing our encoder-decoder architecture has largely been dictated by a lack of resources. We conceptually prefer the more straight-forward training approach of training the prompt model directly on long context data, and removing the positional invariant transformation. Future work could thus increase computational resources and investigate the possibility of different positional encoding schemes.

Finally, we stress that nothing in our approach has focused explicitly on common sense. It is hence expected that methods that do, like KG-BART, perform better on this metric. Future work could thus investigate the use of a prompt model to control a CLM fine-tuned towards common sense, or fine-tune a prompt model using common sense data. Results on CommonGen and C^2GEN dataset still leave ample room for improvements.

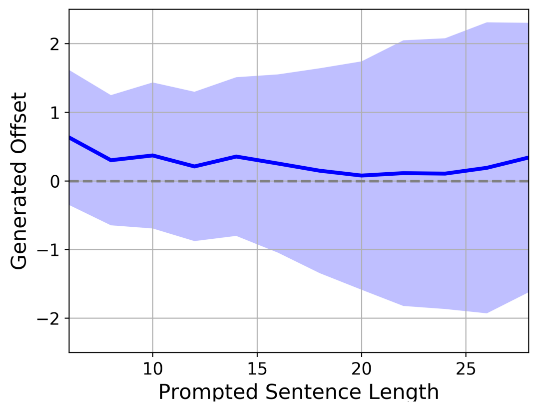

Figure 4: Offset of generated sentence length from prompted sentence length, on the CommonGen validation set. The curve shows the mean offset and the filled area shows the standard deviation.

9 Conclusion

This paper has introduced the concept of non-residual attention and demonstrated how it can be used to control a generative text model. Additionally, our work pinpoints the lack of open-ended controllable text generation tasks that require the model to also account for a given context. We set out to remedy this by introducing the humanly created C^{2}GEN dataset, introducing the task of contextualized word inclusion.

Experimental results on C^{2}GEN and CommonGen, clearly demonstrates that using a non-residual prompt model increases generative control over a CLM. Compared to other methods, our approach stands out as the most versatile, consistently performing well across all tested situations.

Acknowledgements

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Ethical Considerations

Controllable text generation is an important step to unleashing the potential of modern CLMs. Additionally, it is an interesting approach to counter many of the problematic biases that have been found. But an increased level of control also entails an increased risk of malicious use. We hence recognize the possibility that techniques proposed in this paper could be utilized in malevolent scenarios, like guided misinformation or targeted harmful content.

This work has utilized computational GPU resources provided by ICE-RISE[5]. The final model training lasted roughly 2 days on a single DGX-100 machine, resulting in about 400 GPU hours. The total number of GPU hours for the whole research endeavour is difficult to estimate, but it can be safe to assume that it is less than 2000 GPU hours.

[5] https://ice.ri.se/

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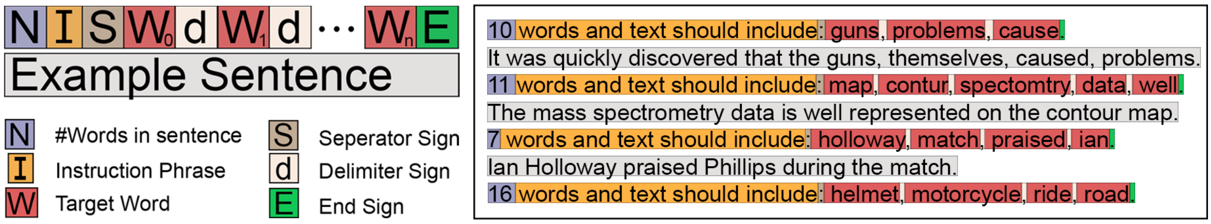

Figure 5: Overview of the random prompt generation template. The left section illustrates the template formula for a single example. The right section demonstrates a full prompt with the target sentence length *"**16**"*, and the target words: ***Helmet***, ***Motorcycle***, ***Ride*** *and* ***Road***. In this case the inclusion phrase was selected to be *"**words and text should include**"*, the separator sign *"**:**"*, the delimiter *"**,**"*, and the end sign *"**.**"*

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A Training Details

A.1 Training Data

Both pre-training phases (step 2 and 3 in Figure 2) are based upon texts from Wikipedia. For the first pre-training phase, we only consider sentences where the number of tokens fulfills: $5 \leq N_{\text{tokens}} \leq 32$. The length of the sentences remaining after this filtering are depicted in Figure 6. In the second pre-training phase, subsequent sentences are packed up until the combined token length reaches 128 tokens. The prompt model is then trained to instruct the CLM for each of the packed sentences made up of $5 \leq N_{\text{tokens}} \leq 32$ tokens. In both phases the number of tokens are given via the GPT-2 Tokenizer (Radford et al., 2018b).

Throughout both pre-training phases we sample $[A = 3, B = 6]$ unique words for each valid sentence, removing the probability of sampling stop words. If a sentence lacks 3 unique non-stop words it is removed from the first pre-training phase, and ignored during the second.

The reason for limiting the training corpus to sentences with a maximum of 32 tokens is to keep the computational burden low, in particular the maximum memory consumption. This is less of a problem in the second pre-training phase, where only the positional invariant transformation is trained, hence removing the need to store an optimizer state for the prompt model's parameters.

A.2 Training Settings

Both pre-training phases use the same set of hyperparameters. The batch size is set to 1280 samples. The maximum learning rate is set to 10^{-4}, following a linear warm up schedule for the first 500 update steps.

The training is performed with early stopping in regards to coverage, on a hold-out validation set. For the first pre-training phase, where the prompt model is trained towards single sentence data, this is done with the CommonGen validation set. In the second phase, a custom validation set created by sequences of Wikipedia sentences is used.

A.3 Randomized Prompt Template

In accordance to the popularized prompt paradigm of (Brown et al., 2020) we start each prompt with a couple of examples, followed by the actual instruction. To increase generalization during the pre-training we procedurally generate prompts where both the included examples and the overall formatting is randomized.

Each prompt includes three examples which are uniformly sampled from a set of 50,000 sentences, which have been randomly selected and set aside from the pre-training dataset. The format is generated by joining the examples, target words and target sentence length, with a set of randomly selected combination tokens. These tokens are randomly selected from a fixed list of candidates. An example of a randomly generated prompt is available in Figure 5.

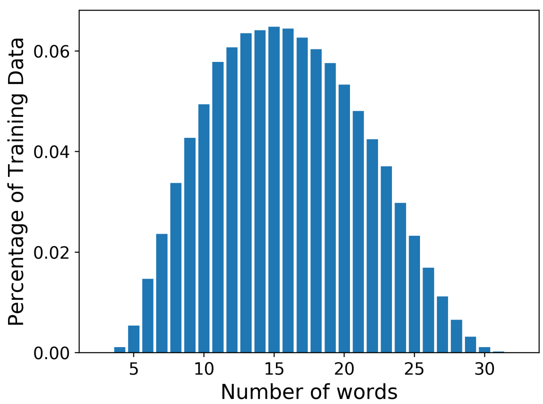


Figure 6: Distribution of sentence length in number of words for the filtered Wikipedia training data.

B Inference Details

B.1 Experiment Configurations

All non-residual prompt models utilize a repetition penalty of 1.25 and beam size of 4. For tasks without context they all start with the word *"The"*. The prompted sentence length for each model is set via hyperparameter search on a held-out validation set. For CommonGen we use the provided validation set, and for the C^{2}GEN dataset we use a portion of the pre-training dataset (Appendix A.1). The selected sentence lengths for each model and setting are available in Table 6.

B.2 Prompting Schema

All word inclusion experiments utilize the same simple inference schema. For each sample a single prompt instruction is generated, including all of the target words and sentence length. The CLM is then allowed to attend to this instruction using non-residual attention, until all target words have been generated. After this the CLM continues entirely using the textual stream, and is thereafter identical to the original CLM. In the free text setting, this means that if the CLM ends a sentence without having included all target words, the prompt instruction is still enabled. An example of this is illustrated in Figure 7.

We recognize that one could investigate a more fine-grained and adaptive approach. For example, one could easily alter the prompt instruction to only cover words that are yet to be included, or extend the target sentence length if not all words are included towards the end. We heavily encourage future work to investigate such approaches. The reason for our simpler approach is to lend more focus to the overall architectural contribution. This also demonstrates how one can easily steer the generation through high level instructions.

B.3 Keyword2Text Incorporation

To test the intuition of aiding the prompt model's high-level planning with direct decoding strategies we supply a slightly modified version of Keyword2Text (Pascual et al., 2021), that we find to work better. This modified version is heavily inspired by the *Max Only* and *No Guarantee* version of Keyword2Text, as we only increase the probability of the target words and by not forcing them to appear. The major difference is that we not only increase the sampling probability for the target words, but also their different lemmas. Word lemmas are extracted from the target words via the use of Spacy (Honnibal et al., 2020).

Model Name	Free Text	Sentence
NRP	10	15
NRP + Keyword2Text	10	15

Table 6: The prompted sentence lengths for both non-residual prompt models, for both the Free Text and Single Sentence setting.

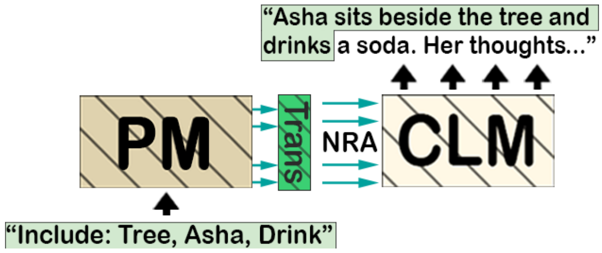


Figure 7: An example of how NRP's Inference Prompting falls back to regular CLM generation when the target words have been successfully included.

The sampling probability modifier is applied in the same fashion as the repetition penalty of (Keskar et al., 2019), where a multiplier is applied on the logits values of the CLM. Target word that has been included have all of its lemmas effectively assigned a sampling probability of zero. Identical to the prompting schema described in Appendix B.2, this additional decoding strategy is deactivated once all the target words are included.

The sampling probability modifier for a non-included target word is given by Equation 2, where α depicts the maximum increase, and λ the inclusion factor dictating the shape of the exponentially increasing modifier curve. T depicts the fraction of completion for the generative process, in regards to the maximum number of generation steps. Hence, T is always within the range $[0, 1]$.

$$1 + \alpha \frac{e^{\lambda T}}{e^{\lambda}} \tag{2}$$

All experiments in this paper utilize the same set of parameters, where $\alpha = 0.5$ and $\lambda = 5.5$. We note that increasing α has the expected effect of increasing overall coverage, but we found this to be at a non-acceptable loss of textual quality.

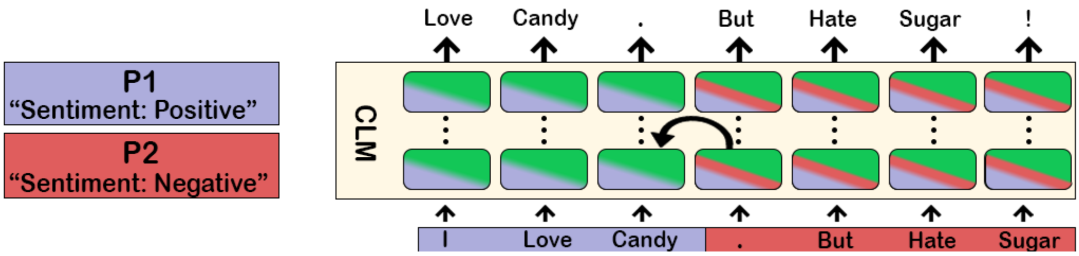


Figure 8: Illustration of the residual prompt effect that can happen in a Casual Language Model. The curved arrow indicates where the CLM should attend to the second instruction, but it is also affected by the first instruction.

C Architectural Motivation

C.1 Residual vs Non-Residual Prompts

As explained in Section 3.1, the non-residual attention hinders an instruction at time step n to influence future time steps via its key-values. If one instead applies prompts directly to the CLM's textual stream, it allows the prompt to have a lingering effect on future decoding steps, where it might not be desired. This is demonstrated in Figure 8, where the second instruction is the exact opposite of the first. To what extent this effect actually occurs in large CLMs is left for future work.

C.2 Positional Invariant Transformation

The positional invariant transformation allows us to both reduce the maximum memory consumption during pre-training and cope with the absolute positional encoding system of GPT-2. Since we only train the positional invariant transformation during the second pre-training phase, the need to store an optimizer state for the prompt model's parameters is alleviated, in turn allowing us to increase the target sequence length without having to increase the computational memory load.[6]

If one is not limited by computational resources, an intuitive alternative approach to is to actively change the positional encoding of the prompt model, to match the current generation step for the CLM. Unfortunately, we find that shifting the prompt model's absolute encodings is problematic in its own way, since this detrimentally impacts the pre-trained CLM's textual abilities. As demonstrated in Table 7, simply shifting the positional input encoding with a single step completely ruins the CLM's generative process.

We hypothesize that this positional frailty is due to the pre-training objective of GPT-2, which positionally encodes each input sequence from 0 and onward. These results lead us to speculate that directly converting a CLM with an absolute encoding system into a positional invariant prompt model forces one to discard a significant portion of the information achieved during the CLM's pre-training, hence severely reducing the benefits of bootstrapping from a pre-trained CLM. Thus, we estimate that such an approach entails both higher maximum memory consumption and also longer training time.

C.3 Results Without Positional Invariant Transformation

The main results displayed in Section 6, are centered around an NRA model which includes a positional invariant transformation. To demonstrate the utility of this transformation we provide results from the same NRA model without this transformation. As demonstrated in Table 8, this causes the generative process to completely collapse as soon as context is added. Hence, we did not perform any further human evaluation.

[6] In our case, we were unable to train the prompt model with longer contexts, due to memory constraints.

Positional Encoding	Generated Text Continuation
$[0, 1, 2, 3, 4, 5, 6, 7, 8]$	"*and she was walking along the path when she saw...*"
$[1, 2, 3, 4, 5, 6, 7, 8, 9]$	"*was was was was was was was was was was...*"
$[8, 9, 10, 11, 12, 13, 14, 15, 16]$	", , , , , , , , , , , ..."

Table 7: Generated text sequences continuing from the text *"Emily was out walking in the park,"* encoded with different absolute positional encoding sequences. The model used is GPT-2 Large with a beam size of 1.

	Free Text (32 Tokens)			Single Sentence		
	Cov ↑	Ppl ↓	Self-Bleu ↓	Cov ↑	Ppl ↓	Self-Bleu ↓
CommonGen (No Context)						
NRP	98.4	14.1	36.1	93.0	24.0	28.4
NRP - No Trans	95.6	19.2	38.2	92.68	30.4	26.0
C^{2}GEN (With Context)						
NRP	96.9	10.0	31.3	81.0	12.3	22.5
NRP - No Trans	6.2	39796	38.4	1.6	41905	33.5

Table 8: Results for the Word Inclusion experiments on CommonGen.

C.4 Cross-Attention vs Non-Residual Attention

In a traditional encoder-decoder architecture the encoder fully processes the input data before any information is passed to the decoder. Admittedly, this makes intuitive sense, but it also entails that the decoder cannot do any computations before the encoder is completely finished. However, using a non-residual attention (or just regular self-attention) encoder, allows the encoder and decoder to execute in parallel, effectively increasing the theoretical inference speed by a factor of 2.

D Extended Related Work

D.1 Decoding Strategies

PPLM incorporates an attribute model (bag of words) in order to steer its CLM. The gradients from the attribute model push the activations within the CLM, increasing the probability of generating the target words. In CommonGen, the concept sets include only a few target words, while PPLM typically have been used with larger bags of words. This could potentially explain its poor coverage in our experiments. Furthermore, PPLM uses a GPT-2 Medium language model while NRP and Keyword2Text are based on the GPT-2 Large. We relied on the example BoW settings provided on the official GitHub page,[7] and the target generation length was modified to 32 tokens.

PPLM incorporates a target generation length, but has no explicit sentence level control. It is thus omitted from all sentence-level experiments.

Keyword2Text directly increases the sampling probability of words semantically similar to the target words. It also provides a guarantee for word inclusion, enabling hard-constrained text generation. However, Keyword2Text is based on word stemming, while the coverage metric relies on lemmatization. This is likely the reason why Keyword2Text does not achieve 100% coverage in our experiments. We used the example ROC Story settings provided on the official GitHub page,[8] and changed the generation length to 32 tokens.

Keyword2Text incorporates a target generation length, but yields no explicit sentence level control. It is thus omitted from all sentence-level experiments.

D.2 Training Strategies

CTRL incorporates genre-specific control codes in its CLM pre-training objective. In this way, the model learns to adapt its generation to fit the target domain and genre. There is not any straightforward way of incorporating the word inclusion objective in this pre-training framework. Hence, we did not deem CTRL a suitable baseline for our experiments.

KG-BART augments a sequence-to-sequence model (BART) with knowledge graphs to enhance its common sense reasoning abilities. It specifically fine-tunes BART on the CommonGen training data, which consists solely of single sentences. This results in the model generating short and succinct sentences, but not being capable of continued text generation. Hence, KG-BART is omitted from the Free Text generation tasks. Moreover, KG-BART is designed to take a concept set as input, and not any additional context. It was hence removed from all experiments on the C^2GEN dataset.

We relied on the official scripts for fine-tuning and inference.[9] During inference KG-BART utilizes a beam search with beam size of 5, along with an n-gram-based repetition constraint.

GDC controls the text generation of a pre-trained CLM by fine-tuning towards point-wise and distributional constraints with policy gradient. Additionally, GDC incorporates a KL-Divergence loss, to keep the fine-tuned model similar to the initial CLM. However, this fine-tuning process is extraordinarily expensive requiring roughly 72 hours to tune a GPT-2 Small model towards a single word. Furthermore, it lacks a setting for general word inclusion and is thus excluded from our experiments.

POINTER solves the word inclusion task in a non-autoregressive manner, iteratively injecting words around the target words. The target words are thus all included prior to the generation process. POINTER can therefore only fail on the coverage task if it combines a target word with another word. It is designed to generate single sentences, and cannot handle contexts without significant modifications. We used the standard decoding script provided on the official GitHub page[10] but changed the separator to ", ".

D.3 GPT Prompting

The currently most popular approach to steering CLM's is via what is called prompting. In this approach the desired instruction is formulated as a textual context, from which the CLM continues. Following the popular paradigm of few-shot prompting, each prompt starts with a number of examples of the word inclusion task. We found that careful tinkering of the prompt layout and the included examples had significant impact on the performance. The final prompt used for the various experiments are available in Appendix H. A beam size of 4 was used during inference for all experiments.

[7]https://github.com/uber-research/PPLM
[8]https://github.com/dapascual/K2T
[9]https://github.com/yeliu918/KG-BART
[10]https://github.com/dreasysnail/POINTER

E Evaluation Metrics

E.1 String Matching as Evaluation Metrics

The current default way of evaluating CommonGen results is to compare the generated sentence with a few label sentences, using standardized string matching metrics such as BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), CIDER (Vedantam et al., 2015), and SPICE (Anderson et al., 2016). While we see the value of such metrics in tasks like machine translation, where there is a constrained number of acceptable text formulations, we intuitively disagree of the usage of these metrics for CommonGen. Controllable text generation with word inclusion allows for vast amounts of creativity, something we believe is easily lost when one is tasked to stay similar to a few label sentences. It is easy to imagine how this evaluation system could unjustifiably penalize creative texts, although they adhere to commonsense. For this reason, we did not evaluate on string matching, and did not collect any label sentences for C^{2}GEN.

E.2 Automatic Metrics

Word Inclusion Coverage is calculated using pattern matching of lemmatized versions of the generated texts (Lin et al., 2020). To avoide the obvious flaw of comparing lemmatized output with non-lemmatized input, we also lemmatize the input words. To further increase the coverage fairness we include all word lemmas using the python packages lemminflect (Jascob, 2019) and Spacy. The correlation between coverage and sequence length varies between models, but longer sequences often provide more space to include the target words.

Perplexity is calculated for the generated token sequence $X = (x_c, x_{c+1}, ..., x_{c+n-1})$, where c depicts the context length. This means, that for the C^{2}GEN dataset the perplexity is conditioned on the context, while $c = 0$ for the original CommonGen. Perplexity is strongly correlated with sentence length, meaning that both longer context and longer generated texts decreases perplexity. All our perplexity calculations utlize GPT-2XL, and follows the formula below.

$$\exp\left\{-\frac{1}{n}\sum_{i=c}^{c+n-1}\log p_\theta\left(x_i \mid x_{<i}\right)\right\}$$

Self-BLEU-5 (Zhu et al., 2018) evaluates the syntactic diversity of a given set of texts. It is defined as the average BLEU-5 (Papineni et al., 2002) between all text pairs in the given set. Due to BLEU measuring the ratio of overlap, longer sequences tend to yield lower Self-BLEU scores, as it is less likely that two long texts completely overlap.

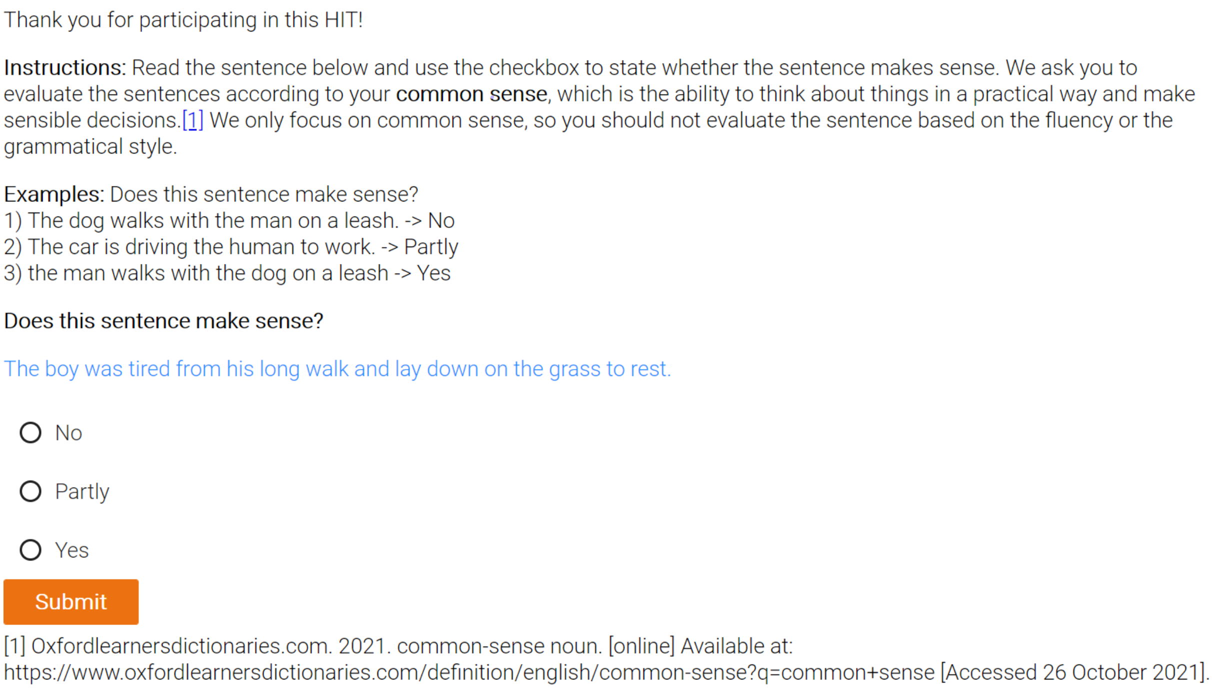
E.3 Human Evaluation Metrics

For each experimental setting, 100 generated texts are sampled from each algorithm. These samples are evaluated by humans on *common sense*, and in the case of C^{2}GEN, also *contextual relevance* (see definitions below). Using Amazons Mechanical Turk, each sample received 5 unique native English judges for both common sense and contextual relevance. Meaning that samples in C^{2}GEN were evaluated first by 5 judges on common sense, then independently judged by 5 potentially other judges on contextual relevance.

For both metrics, the annotators were tasked to answer either *"Yes"*, *"Partly"*, or *"No"*, as demonstrated in Figure 9. These responses were then mapped to the scalar values '*1*', '*0.5*' or '*0*', which resulted in an inter-annotator agreement of 0.51, and a Fleiss' κ of 0.115 (Celikyilmaz et al., 2020). A detailed depiction of the annotations for CommonGen is available in Table 9.

Common Sense is calculated as the overall average of all human annotators for the selected 100 samples. The final reported scores in Table 2 and Table 3 are hence each the average of 500 annotations. To ensure that common sense is separated from contextual relevancy, only the generated text is displayed to the human annotators. Meaning that for C^{2}GEN, the common sense annotators cannot consider the context in which the text has been generated.

Contextual Relevance (CTX) is calculated as an average identically to the common sense score. The only difference is that the annotators are tasked to consider how well the generated texts adheres to the given context, without considering if it makes sense or not.


Thank you for participating in this HIT!

Instructions: Read the sentence below and use the checkbox to state whether the sentence makes sense. We ask you to evaluate the sentences according to your common sense, which is the ability to think about things in a practical way and make sensible decisions.[1] We only focus on common sense, so you should not evaluate the sentence based on the fluency or the grammatical style.

Examples: Does this sentence make sense?
1) The dog walks with the man on a leash. -> No
2) The car is driving the human to work. -> Partly
3) the man walks with the dog on a leash -> Yes

Does this sentence make sense?

The boy was tired from his long walk and lay down on the grass to rest.

No

Partly

Yes

Submit

[1] Oxfordlearnersdictionaries.com. 2021. common-sense noun. [online] Available at: https://www.oxfordlearnersdictionaries.com/definition/english/common-sense?q=common+sense [Accessed 26 October 2021].

Figure 9: An example of a human intelligent task on MTurk. The evaluator is instructed to classify the level of common sense of a generated sentence.

CommonGen	**Free Text (32 Tokens)**		**Single Sentence**	
	Sense	Ctx	Sense	Ctx
GPT-2 Large + Prompt	0.001/0.411	-	0.356/0.653	-
PPLM	-0.024/0.493	-	-	-
Keyword2Text	0.021/0.358	-	-	-
POINTER	-	-	0.230/0.50	-
KG-BART	-	-	0.237/0.698	-
NRP	0.076/0.422	-	0.142/0.575	-
NRP + Keyword2Text	0.087/0.452	-	0.102/0.548	-
C^2GEN				
GPT-2 Large + Prompt	-0.003/0.552	-0.007/0.465	0.312/0.802	0.257/0.445
PPLM	0.023/0.493	0.018/0.477	-	-
Keyword2Text	-0.025/0.442	-0.021/0.463	-	-
NRP	0.049/0.438	-0.033/0.449	0.2073/0.693	-0.040.537
NRP + Keyword2Text	0.039/0.445	-0.029/0.462	0.219/0.688	-0.033/0.566

Table 9: The IAA of the human evaluation experiments. Each cell contains the Fleiss' κ and percent agreement, respectively.

	Cov ↑	Ppl ↓	Self-Bleu ↓
GPT-2 Large Free Text (32 Tokens)	4.6	7.3	43.2
GPT-2 Large Single Sentence	3.8	7.5	37.9

Table 10: The results on the C^{2}GEN dataset with the GPT-2 Large model prompted with the context only, i.e. no prompted instruction on the target words. This provides a simple baseline on how likely the target words are to appear naturally, when the model only focuses on generating a natural continuation of the context.

F Dataset C^{2}GEN

The C^{2}GEN dataset is mainly constructed in accordance with the data in the CommonGen test set. However, minor modifications were made to the distribution of the number of word targets per sample. The CommonGen test set only consists of samples with 4 or 5 target words, while the training and validation data includes samples with only 3 target words. After careful reading we found no argument for this, and speculate that it is purposefully intended to make the task more difficult. Artificially increasing task difficulty by skewing the test set away from the intended training data is however not something which we intuitively agree with.

To remedy this discrepancy, certain words were removed from samples in the CommonGen test set, resulting in all set sizes being equally represented. This results in a more similar and fair distribution between C^{2}GEN, and the CommonGen train and dev split. The filtering of words from the CommonGen test set did however result in a small number of samples being identical. These samples were deduplicated, which resulted in C^{2}GEN being slightly smaller than the CommonGen test set. However, as can be seen in Table 11, this discrepancy is insignificant.

To ensure the quality of the data generation, only native English speakers with a recorded high acceptance were allowed to participate. Finally, all contexts were manually verified, and fixed in terms of typos or poor quality.

The context lengths of the collected dataset are visualized in Figure 10. The perplexity and the Self-Blue metrics of the texts are available in Table 11. To evaluate the probability of the target words appearing naturally in a textual continuation, we use GPT-2 to generate text without the given target words and report on the coverage in Table 10.

Statistic	CommonGen	C^{2}GEN
# Concept-Sets	1,497	1,483
- Size = 3	-	494
- Size = 4	747	496
- Size = 5	750	493
# Unique Concepts	1,248	1,122
# Unique Concept-Pairs	8,777	6,835
# Unique Concept-Triples	9,920	6,959
% Unseen Concepts	8.97%	7.75%
% Unseen Concept-Pairs	100.00%	100.00%
% Unseen Concept-Triples	100.00%	100.00%
	C^{2}GEN	
Average context-sentence length	43.92 ± 10.32	
Perplexity (GPT-2 XL)	21.93	
Self-Bleu	16.63	

Table 11: A statistical comparison between the original CommonGen test dataset and the C^{2}GEN dataset.

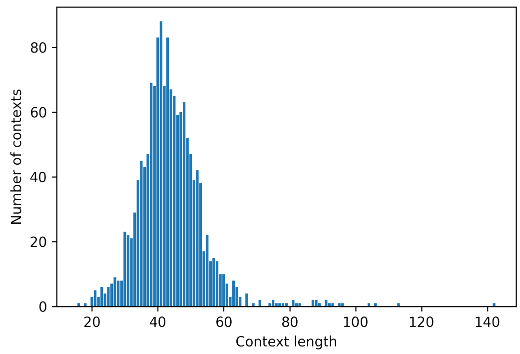


Figure 10: Distribution over number of words in the context of the C^{2}GEN.

G Qualitative Examples

	NRP
1	The players **sit** in **front** of a **microphone**, with the **guitar** and drums on one side of them.
2	The most common **use** of the **tool** is to remove a **piece** of **metal** or plastic from an object, such as a door knob.
3	The **dog** **walks** on a **leash**, and the owner can **walk** their pet on the **sidewalk** or in front of their home.
	GPT2-Large
1	The **guitar** was on the **front** of the sofa.
2	The **piece** of **metal** was **used** in the **tool**.
3	The **dog** was **walking** on the **sidewalk**.
	POINTER
1	he is shown **sitting** in **front** of a stage, playing his **guitar**, and standing behind a **microphone** on the one where he had to **sit** in the back.
2	, also known as a **metal** plate or, is a **piece** of **metal**, a sharp **tool**, that can be removed with the **use** of other **tools**.
3	this allows a **dog** that has been on a **leash** to be lowered onto the **sidewalk**, or to **walk** along the **sidewalk**.
	KG-BART
1	A man with a **guitar** **sits** in **front** of a **microphone** and plays his **guitar**.
2	A man **uses** a **tool** to remove a **piece** of **metal** from a **metal** **piece** of wood.
3	A **dog** **walks** on a **leash** on a **sidewalk**.
	PPLM
1	The new year is just around the corner, and with it comes a plethora of new releases and albums, but this year's lineup is the most impressive we've
2	The United States is one of only a few industrialized democracies which allow its citizens to buy and **use** drugs on behalf of their patients, and to provide them with a
3	The "Boomer" and "Boomer-Bom" are two words that mean very different things. When you say something to a person that
	Keyword2Text
1	Right **front** corner of the **guitar**.\n\n\nSituation: You are holding a **microphone** in one hand while playing a **guitar**.\n\n\nReason for selecting the
2	**Metal** Gear Solid V: The Phantom Pain **use** a **tool** called **Metal** Gear Solid V **Tools** to **piece** together the main storyline. **Metal** Gear Solid V: The Phantom Pain
3	Ad **leash** for **dogs**\n\n\n**Dog** **walkers** and **dog** **walkers** with **sidewalk** **dog** kennels\n\n\nThose of you that own or rent commercial **dog**

Table 12: Generated texts for 3 samples of the CommonGen Test set for the different methods. The inclusion words for the samples are the following; 1: [**front**, **guitar**, **microphone**, **sit**], 2: [**metal**, **piece**, **tool**, **use**], 3: [**dog**, **leash**, **sidewalk**, **walk**], highlighted in blue, red, and green respectively. For models that are evaluated on both Free Text and Single Sentence, the sentence variant is shown.

H GPT Prompt Templates

1. Include the words [eat, hay, horse]: The horse was hungry and went down to the other animal in the barn to eat hay.

2. Include the words [computer, scientist, office]: In the office at this time of day, one could see a large group of enthusiastic scientists sitting by their computers.

3. Include the words [lawn, mow, noon, day]: David had to mow the lawn by noon, he had worked all day and started to get really exhausted.

4. Include the words [soccer, sit, sofa, chance]: The whole group got the chance to sit down on the sofa before the soccer game.

5. Include the words [dog, cat, dirt, floor, window]: The floor was full of dirt after the dog had chased the cat out of the window.

6. Include the words [<words>]:

Figure 11: Prompt template used with GPT2-Large for sentence-level CommonGen text generation.

1. Include the words [eat, hay, horse]: The horse was hungry and went down to the other animal in the barn to eat hay. There they stood, as every evening at this time, eating hay. It was warm and cozy in there, so she joined them and felt very welcomed. After a while, when she was done, she went out for a run with the other horses.

2. Include the words [computer, scientist, office]: In the office at this time of day, one could see a large group of enthusiastic scientists sitting by their computers. They looked calm and at peace, knowing that they were contributing to something great.

3. Include the words [lawn, mow, noon, day]: David had to mow the lawn by noon, he had worked all day and start
ed to get really exhausted. He had one last yard before he could go home and finally sleep. There was no doubt that this was much needed after so many hours of work.

4. Include the words [soccer, sit, sofa, chance]: The whole group got the chance to sit down on the sofa before the soccer game. Tommy entered the room, holding a plate full of beers for everyone. They all shouted in joy for the beverages they were going to drink, one of them even fell off the couch.

5. Include the words [dog, cat, dirt, floor, window]: The floor was full of dirt after the dog had chased the cat out of the window. Even the rug had been torn to pieces after the rough chase of the cat. He was surprised when he came home and opened the door, despite the mess he smiled lovingly.

6. Include the words [<words>]:

Figure 12: Prompt template used with GPT2-Large for 32 Token CommonGen text generation.

1. The horse was hungry and went down to the other animal in the barn. There they stood, as every evening at this time, eating hay. It was warm and cozy in there, so she joined them and felt very welcomed.
Include the words [run, rain, horse]: After a while, when she was done, she went out for a run with the other horses in the rain.

2. In the office at this time of day, one could see a large group of enthusiastic scientists sitting by their computers. They looked calm and at peace, knowing that they were contributing to something great. Suddenly, the CEO walked in.
Include the words [employee, furious, room]: He was furious with one particular employee and asked him to follow him to the conference room.

3. David had to mow the lawn by noon, he had worked all day and started to get really exhausted. He had one last yard before he could go home and finally sleep. There was no doubt that this was much needed after so many hours of work.
Include the words [dream, game, play, night]: He was dreaming about his younger days when he could play games with his friends every night.

4. The whole group got the chance to sit down on the sofa before the soccer game. Tommy entered the room, holding a plate full of beers for everyone. They all shouted in joy for the beverages they were going to drink, one of them even fell off the couch.
Include the words [point, laugh, stand]: His friends laughed and pointed at him before they decided to help him stand up.

5. The floor was full of dirt after the dog had chased the cat out of the window. Even the rug had been torn to pieces after the rough chase of the cat. Stacy was surprised as she came home and opened the door, despite the mess she smiled lovingly.
Include the words [treehouse, shoulder, look, jump, pet]: She looked outside by the treehouse to make sure everything was alright when suddenly her pet jumped down and landed on her shoulder.

6. She had been hugged by a complete stranger. She also thought she had been called a thief, whatever the reason for this was. She was confused.
Include the words [sprint, imagine, imagination, bicycle]: She sprinted to her bicycle and set off for home, hoping she was imagining it all, which she had never dared to think before, because she did not like the thought of imagination.

7. <context>
Include the words [<conceptSet>]:

Figure 13: Prompt template used with GPT2-Large for C^{2}Gen text generation.