

Visualize Before You Write: Imagination-Guided Open-Ended Text Generation

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Abstract

Recent advances in text-to-image synthesis make it possible to visualize machine imaginations for a given context. On the other hand, when generating text, human writers are gifted at creative visualization, which enhances their writings by forming imaginations as blueprints before putting down the stories in words. Inspired by such a cognitive process, we ask the natural question of whether we can endow machines with the same ability to utilize visual information and construct a general picture of the context to guide text generation. In this work, we propose iNLG that uses machine-generated images to guide language models (LM) in open-ended text generation. The experiments and analyses demonstrate the effectiveness of iNLG on open-ended text generation tasks, including text completion, story generation, and concept-to-text generation in few-shot scenarios. Both automatic metrics and human evaluations verify that the text snippets generated by our iNLG are coherent and informative while displaying minor degeneration.¹

1 Introduction

One great resource human writers cherish is the ability of imagination, with which they render mental images about an actual or vicarious experience and link knowledge that would later make the writing more concrete, sensible, and intriguing. Cognitive studies show that visual imagery improves comprehension during language processing (Gambrell and Bales, 1986; Joffe et al., 2007; Sadoski and Paivio, 2013), and that mental imagery facilitates humans’ written language expression at young ages (Gambrell and Koskinen, 2002).

When it comes to the study of Artificial Intelligence (AI), one classic challenge for AI systems is to generate informative and coherent text snippets. Open-ended text generation is such a task that provides an input context, and asks the model to generate a piece of text that is consistent with the

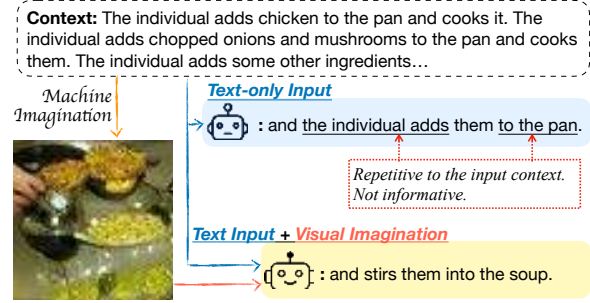


Figure 1: When performing open-ended text generation, the language models prompted with text-only input may generate repetitive or unilluminating contents, which is also known as degeneration. Hereby, we propose to use machine-generated images as additional visual supervision to guide the language models in generating more informative and coherent text with the given context.

context. This is the cornerstone of a wide range of downstream tasks such as text completion (Guan et al., 2019; Radford et al., 2019), story generation (Fan et al., 2018; Goldfarb-Tarrant et al., 2020; Swanson et al., 2021; Su et al., 2022b), and dialogue systems (Schatzmann et al., 2007; Wen et al., 2015, 2017; Wei et al., 2018; Wu et al., 2021), and has received much attention throughout the years. Inspired by human writers’ common practice of creative visualization, we ask the following question: Can we endow machines with the same ability to construct a general picture of the context and use it as a blueprint to guide text generation?

Recent advances in text-to-image generation make it possible to visualize machine imaginations for a given context (Ramesh et al., 2021; Rombach et al., 2021; Crowson et al., 2022b; Wang et al., 2022b; Saharia et al., 2022). Moreover, this line of work shows great potential in utilizing textual information to guide image synthesis. It comes naturally that one may attempt to complete the loop by using visual supervision to guide text generation.

In this work, we propose using machine-generated images to guide the language model

¹Our code & data: <https://github.com/VegB/iNLG>.

(LM) in open-ended text generation. More specifically, we visualize machine imagination for the input context by rendering images with a state-of-the-art text-to-image generator OFA (Wang et al., 2022b). The machine imagination act as additional visual supervision to guide the LM in generating more informative and coherent text in two ways. Firstly, the machine-generated images are introduced as the input to the LM in the form of the visual prefix. Secondly, we designed a contrastive training objective that enforces the generated text to be semantically similar to the visual supervision.

We conduct experiments on three open-ended text generation tasks, namely text completion, story generation, and concept-to-text generation, with two popular LM base models, including GPT-2 (Radford et al., 2019) and BART (Lewis et al., 2020). Extensive experiments in the few-shot settings show better or competitive performance to state-of-the-art baselines on both automatic metrics and human evaluation.

Our main contributions are as follows:

- We introduce a novel paradigm that leverages machine-generated images to guide open-ended text generation. This endows the machines with the ability of creative visualization that human writers often demonstrate.
- We distill the vision information from the pre-trained multimodal models and further construct visual prefix to guide language models performing text generation with teacher forcing and contrastive objective.
- Extensive experiments show the effectiveness of iNLG in open-ended text generation tasks, including text completion, story generation, and concept-to-text in few-shot settings.

2 Related Work

Open-ended Conditional Text Generation is the task of generating a coherent portion of the text based on the given context. Recent advances in pre-trained models have pushed frontier in the open-ended conditional text generation, such as text completion (See et al., 2019; Ippolito et al., 2020), story generation (Guan et al., 2020; Fan et al., 2018; Yao et al., 2019) and concept-to-text generation (Zhou et al., 2021; Liu et al., 2021). Despite the success of large language models, text degeneration and semantic coverage still remain as two core technical challenges in few-shot open-ended text generation. To improve the text cover-

age, StoryEndGen (Guan et al., 2019) leverages the knowledge graph to encode context sequentially. Fan et al. (2018) and Yao et al. (2019) plan the content (premise or keywords) first and then encourage the generation based on planned content. To mitigate the text degeneration, SimCTG (Su et al., 2022b) uses a contrastive training strategy to encourage the model to learn isotropic token embeddings. Similar to our approach, Wang et al. (2022a) generates a scene graph for each concept and combines them with text for the model input. Previous work has proposed to add visual information to LM by retrieving images from the Internet or large-scale image sets (Su et al., 2022a). However, the retrieved images may fail to fully incorporate the context, which will misguide the LM from yielding contextually consistent predictions.² Unlike prior work, our approach leverages images generated conditioning on the context to assist the text generation process.

Visually-aided NLP Recent work show the power of visual guidance in natural language processing, spanning from the language representation learning (Lu et al., 2019; Li et al., 2019; Sun et al., 2019; Luo et al., 2020; Chen et al., 2020; Li et al., 2020; Tan and Bansal, 2020; Lu et al., 2022), the downstream tasks (Grubinger et al., 2006; Elliott et al., 2016; Xie et al., 2019; Christie et al., 2016; Shi et al., 2019; Lu et al., 2022) and evaluation (Zhu et al., 2021). They either leverage visual information from the external vision-and-language corpus or obtain such visual knowledge from the large-pre-trained model. In this line of work, imagination achieves promising performance in various NLP domains (Long et al., 2021; Zhu et al., 2021; Wang et al., 2021; Lu et al., 2022). Given the natural human behavior of visualizing before writing, we also endow text generation with visual imagination by generating visual context. Compared to the existing work on pure-language-based text generation (Yao et al., 2019; Su et al., 2022b), our work achieves a breakthrough in few-shot performances with generated visual guidance. Previous imagination-based work in NLP either study the non-generation problems (Zhu et al., 2021; Lu et al., 2022) or utilizing non-visual information (Long et al., 2021; Wang et al., 2021). Our work explores the potential of generating visual imagination to improve the open-ended text generation tasks.

²Figure 8(a) shows examples where the image retrieved from the search engine is irrelevant with the input context.

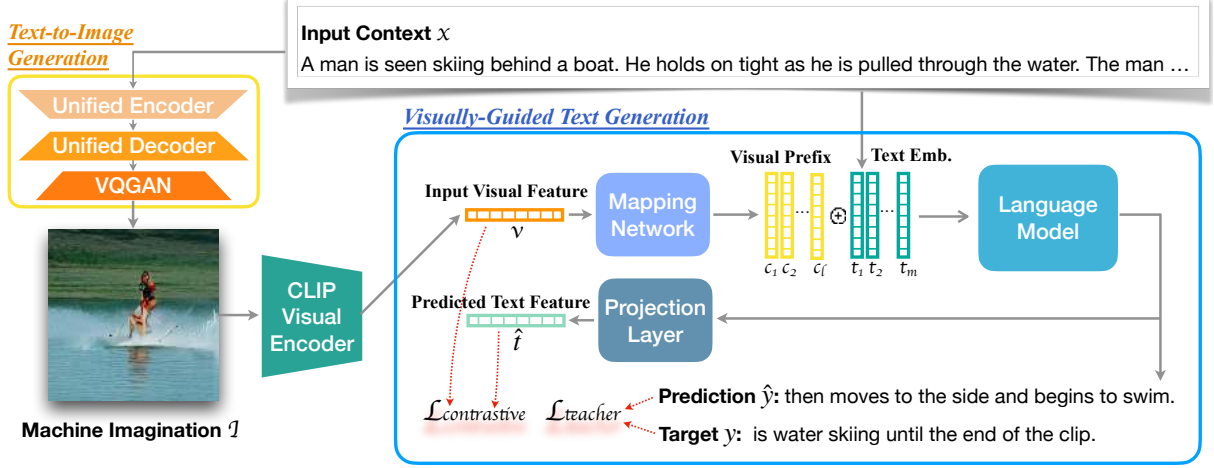


Figure 2: An overview of our iNLG. Given an input context x , we first visualize the context with the text-to-image generation model. Then we use the machine-generated image I as the additional visual supervision to guide the language model in open-ended text generation. The visual feature is provided as a source of input to the LM in the form of the visual prefix. Aside from the teacher forcing objective $\mathcal{L}_{\text{teacher}}$, we also enforce the LM to generate text that is semantically similar to the machine imagination with a contrastive training objective $\mathcal{L}_{\text{contrastive}}$.

3 Method

3.1 Overview

Open-ended text generation is a task that provides an input context, and asks the model to generate a piece of text that is consistent with the context.

This work mainly focused on introducing machine-rendered images to assist LM in performing open-ended text generation. More specifically, given the context x^i , we first use a text-to-image generator to illustrate an image I^i that depicts the input context. The LM is prompted with image I^i as the visual prefix along with the text context x^i , and will incorporate the multimodal input to generate the output text y^i .

Figure 2 provides an overview of our iNLG framework, which mainly involves two modules. The first module is a text-to-image generator that takes in the input context and illustrates a descriptive image, which we also refer to as the machine imagination. The second module is a visually-guided language model that utilizes the machine imagination as a source of input and also a supervision that encourages the LM to generate text that is semantically similar to the visual information.

3.2 Text-to-Image Rendering

In this work, we propose to use images generated conditioning on the context by the machines as additional visual information to the LM. The text-to-image generation backbone is OFA (Wang et al., 2022b), a pre-trained multimodal model that

unifies multimodal inputs in a Transformer-based sequence-to-sequence learning framework. On the input side, visual information are represented as patch features encoded by ResNet (He et al., 2016; Wang et al., 2022c; Dai et al., 2021). On the target side, OFA use quantized encoding for the images (van den Oord et al., 2017; Esser et al., 2021), and refer to as the sparse code.

One of its pretraining task is image infilling (Bao et al., 2022),³ in which the input is an image with the center being masked out, and the instruction of “What is the image in the middle part?”. The model learns to generate sparse codes for the central part of the corrupted image. OFA uses the sparse code of VQGAN (Esser et al., 2021) as the ground-truth labels for training. During inference, the input for OFA is an instruction of “What is the complete image? Caption: context”, where context is the input context for text-to-image generation. Then OFA uses VQGAN to further decode the predicted sparse code into an image.

3.3 Visually Guided Text Generation

Visual Prefix Construction One can encode the visual information with the pre-trained visual models. However, such visual embedding may lie in a representation space different from the LM due to the discrepancy between models. One way of introducing features extracted by another network to the

³Conducted on images from OpenImages (Kuznetsova et al., 2020), FCC100M (Thomee et al., 2016) and ImageNet-21K (Deng et al., 2009).

current model is through feature mapping (Mokady et al., 2021). With a dataset of image-text pairs (I', x') , we can pre-train a mapping network \mathcal{F} for a given LM in an image captioning formulation. More specifically, we encode I' with the visual encoder $\text{Enc}_{\text{visual}}$ and receive its visual features v' . Then we apply the mapping network \mathcal{F} over v' , and receive a sequence of l visual prefix:

$$c'_1, c'_2, \dots, c'_l = \mathcal{F}(v') = \mathcal{F}(\text{Enc}_{\text{visual}}(I')) \quad (1)$$

We provide the list of visual prefix as input to the LM with the corresponding text x' as the target output. Such a pre-training process enables \mathcal{F} to project visual features into the visual prefix that lies within the same embedding distributions as the LM. The mapping network is agnostic of the downstream task, and only depends on the visual source and the LM.

After generating a descriptive image I^i for the input context x^i , we use CLIP to encode I^i and receive its visual features v^i . We apply the pre-trained mapping network \mathcal{F} over v^i , and receive the visual prefix c^i of length l :

$$c^i = \{c_1^i, c_2^i, \dots, c_l^i\} = \mathcal{F}(\text{CLIP}(I^i)) \quad (2)$$

Visually-guided Language Modeling We use the visual information to guide text generation in two ways, reflected in the following two training objectives.

Firstly, we directly introduce the machine generated visual information as input to the LM. We concatenate the visual prefix c^i and the text embeddings t^i for the input context x^i with m tokens. LM input can be denoted as $[c^i; t^i] = \{c_1^i, \dots, c_l^i, t_1^i, \dots, t_m^i\}$. With the target output $y^i = \{y_1^i, y_2^i, \dots, y_n^i\}$ and θ denoting the trainable parameters, we can list out the teacher forcing training objective as follows:

$$\mathcal{L}_{\text{teacher}} = - \sum_{j=1}^n \log p_{\theta}(y_j^i | c^i; t^i; y_{<j}^i) \quad (3)$$

In addition, we design a contrastive objective to enforce the generated text to be semantically similar to the input visual supervision with the InfoNCE loss (van den Oord et al., 2018):

$$\mathcal{L}_{\text{contrastive}} = - \log \frac{\exp(\text{sim}(v^i, \hat{t}^i)/\tau)}{\sum_{j \neq i} \exp(\text{sim}(v^i, \hat{t}^j)/\tau)} \quad (4)$$

in which \hat{t} is the projected representation of the decoder’s last layer’s output, and can be viewed as the sentence-level representation for the generated text. Here $\text{sim}(\cdot, \cdot)$ first normalize the two vectors, then compute their cosine similarity, and τ is the temperature.

3.4 Training & Inference

We first pre-train the mapping network on the pre-training dataset with the teacher forcing objective. Such pre-training is agnostic of the downstream task, and only depends on the type of base LM.

When applying our iNLG on downstream tasks, we train the base LM with the teacher forcing objective for the first $N_{\text{no_contra}}$ epochs. Then, we introduce the contrastive objective and tuning the base LM together with the mapping network and projection layer by minimizing the following loss \mathcal{L} . Here ep denotes the epoch and λ is the factor:

$$\mathcal{L} = \begin{cases} \mathcal{L}_{\text{teacher}}, & ep < N_{\text{no_contra}}, \\ \mathcal{L}_{\text{teacher}} + \lambda \mathcal{L}_{\text{contrastive}}, & ep > N_{\text{no_contra}}, \end{cases} \quad (5)$$

During inference, we provide the context and machine-generated image to the LM. We use beam search during decoding with a beam width of 10.

4 Experimental Setup

4.1 Tasks, Datasets, and Baselines

We apply our iNLG on three open-ended text generation setups: sentence completion, story generation, and concept-to-text generation. Table 1 shows examples for each task.

Sentence Completion is a task of finishing the sentence in a commonsense inference scenario. We conduct experiments on the ActivityNet (Heilbron et al., 2015) subset⁴ of HellaSwag (Zellers et al., 2019), which is a benchmark for commonsense natural language inference that ask the model to predict the most likely follow-up among several choices given a specific context. We compare with StoryEndGen (Guan et al., 2019) which encodes the given context incrementally and attends to the one-hop knowledge graph retrieved from ConceptNet for the context tokens. GPT-2 (Radford et al., 2019) by nature, can generate the follow-up for an arbitrary input in a zero-shot manner. We implement our iNLG on top of the GPT-2-base.

⁴14740/982/2261 samples for train/validation/test.

Task	Input Context	Target Output
Text Completion	Different people are interviewed on camera while several others are shown raking up the leaves. A man is seen sitting in his car and another puts his gloves on. The camera	pans over the raked up leaves while several others discuss their hard work.
Story Generation	Live Show. Tim was in his school’s play.	He was nervous about their first show. He almost dropped out. The show went smoothly. Tim was excited for his second show.
Concept-to-Text	grow, flower, pavement	Wild flower growing through crack in the tiled pavement.

Table 1: Input context and corresponding target output exemplars for three open-ended text generation task, namely story generation, text completion, and concept-to-text generation.

Story Generation requires the model to compose a story based on the given title or context. We conduct experiments on the widely used story generation benchmark ROCStories (Mostafazadeh et al., 2016). Each data item consists of a story title and a human-written five-sentence everyday life story that incorporates commonsense related to the title.⁵ We provide the story title and the story’s first sentence as the input context, and ask the LM to predict the following four sentences. We consider the following methods as baselines: Action-Plan (Fan et al., 2018) first predicts the premise of a story with the convolutional LM (Dauphin et al., 2017), then use the fusion mechanism (Sriram et al., 2018) to encourage a convolutional seq2seq model (Gehring et al., 2017) to generate the story from the premise. Plan-and-Write (Yao et al., 2019) first plans a storyline that consists of keywords, then generate the story conditioned on the storyline. Its model structure is built upon GRU (Cho et al., 2014). SimCTG (Su et al., 2022b) proposes a contrastive training objective that encourages the LM to learn discriminative and isotropic token representations, and is implemented on GPT-2 (Radford et al., 2019).

Concept-to-Text is a relatively more constrained conditional text generation task involving commonsense reasoning. This task provides a set of concepts as input, and requires the model to generate a piece of text that incorporates the concepts and describes an everyday scenario. We conduct experiments on the CommonGen (Lin et al., 2020) benchmark.⁶ We compare against the following models: KG-BART (Liu et al., 2021) encompasses the relations of concepts with the knowledge graph and augments the BART (Lewis et al., 2020) encoder and decoder with graph representations. Mode-

lAdapt (Ma et al., 2021) is built upon BART and removes the positional embedding in the encoder. Imagine-and-Verbalize (I&V) (Wang et al., 2022a) predicts a scene graph for each set of concepts, and uses it as an additional input to the LM. In contrast to I&V, we directly visualize the concepts and use the machine-generated images as the auxiliary information to assist the concept-to-text generation.

4.2 Evaluation

Automatic For sentence completion and story generation, we follow previous work and evaluate the quality of the generated text from the aspect of model degeneration level (rep- n , diversity, distinct- n), text distribution divergence (MAUVE), and semantic similarity (BERTScore): (1) rep- $n = 1.0 - \frac{|\text{unique } n\text{-grams}|}{|\text{total } n\text{-grams}|}$ measures sequence level repetition by computing the portion of duplicate n -grams (Welleck et al., 2020). (2) diversity = $\prod_{n=2}^4 (1 - \text{rep-}n)$ measures the diversity of n -grams (Su et al., 2022c). (3) distinct- $n = \frac{|\text{unique } n\text{-grams}|}{|\text{length of text}|}$ measures the portion of distinct n -grams in the text (Li et al., 2016). (4) MAUVE measures the learned distributions divergence between the generated text and human-written text (Pillutla et al., 2021).⁷ (5) BERTScore assesses contextual text similarity between two pieces of texts by computing the cosine similarities between their tokens’ embeddings (Zhang* et al., 2020).⁸

For concept-to-text, following prior work, we report the metrics scores on BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), CIDEr (Vedantam et al., 2015), SPICE (Anderson et al., 2016), and BERTScore (Zhang* et al., 2020).

Human We also set up a human evaluation as a complementary evaluation beyond the automatic metrics. We select 100 samples from the test set for sentence completion and story generation and perform the head-to-head comparison between the

⁵We use the split provided by Su et al. (2022a), which is based on the ROCStories Winter 2017 release and contains 49666/1500/1500 items for the train/validation/test sets.

⁶We use the inhouse split provided by Wang et al. (2022a), which contains 65323/2066/4018 samples for train/validation/test.

⁷We report MAUVE with gpt2-large as the base model.

⁸We report BERTScore with roberta-large as base model.

Task	*	Setting	rep-2 ↓	rep-3 ↓	rep-4 ↓	diversity ↑	distinct-2 ↑	MAUVE↑	BERTScore↑
Sentence Completion	0	Human	0.45	0.05	0.01	99.50	77.32	-	-
	1	GPT2 <i>no finetune</i> (Radford et al., 2019)	6.71	6.87	10.13	78.07	74.83	44.19	22.57
	2	StoryEndGen (Guan et al., 2019)	39.53	35.11	39.30	34.12	44.57	0.45	-47.29
	3	GPT2 <i>text-only finetune</i>	4.20	4.03	5.53	86.85	75.14	49.45	24.13
	4	GPT2 +iNLG	2.24	2.22	3.14	92.58	76.16	61.56	24.26
Story Generation	5	Human	1.76	0.38	0.15	97.71	56.34	-	-
	6	GPT2 <i>no finetune</i>	37.65	22.76	21.92	45.67	43.42	0.43	-7.77
	7	Action-Plan (Fan et al., 2018)	52.05	35.58	28.11	26.97	21.43	0.41	-18.32
	8	Plan-and-Write (Yao et al., 2019)	45.22	32.86	23.34	30.71	20.83	0.41	-37.35
	9	SimCTG (Su et al., 2022b)	28.72	24.02	20.61	43.00	42.06	0.43	18.01
	10	GPT2 <i>text-only finetune</i>	25.41	18.51	14.41	52.10	46.60	9.10	21.23
	11	GPT2 +iNLG	10.90	5.90	3.70	80.73	51.89	33.22	22.02

Table 2: Generation quality scores for few-shot text completion on the ActivityNet and few-shot story generation on ROCStories. “Human” shows the human performance and “GPT2 *no finetune*” denotes the vanilla GPT2 model without tuning. All the other listed models are trained with 1% of the training data. “+iNLG” denotes introducing machine-generated images on top of the base LM.

text snippets generated by our iNLG and the baseline models. We invite human annotators to compare the text quality from the following three independent aspects: (1) *Coherence*: Which snippet is more semantically consistent with the context, and follows the logic of the context more naturally. (2) *Fluency*: Which snippet is more fluent in English. (3) *Informativeness*: Which snippet contains more interesting contents, and describes the scenes that are more likely to happen in real life. Three human judges rate each comparison.

4.3 Implementation Details

We use the OFA (Wang et al., 2022b) to render a 256x256 image from the context, and use CLIP ViT/B-32 to extract features offline. The mapping network is an 8-layer Transformer, and the visual prefix length is 20. For the sentence completion and story generation tasks, the base LM is GPT-2-base (Radford et al., 2019), and the mapping network is pre-trained on the MSCOCO (Lin et al., 2014) dataset. For the concept-to-text task, we test it with BART-base (Lewis et al., 2020) as the base LM, and the mapping network is pre-trained on VIST (Huang et al., 2016).⁹ We pre-train the mapping network for 5 epochs with a batch size of 128. We adopt the few-shot setting for each downstream task and train the models on 1% of the training data for 20 epochs with a batch size of 8. Few-shot training results are reported on three repeat runs. Detailed hyperparameters are listed in the Appendix.

⁹CommonGen is built upon image and video captioning datasets including MSCOCO. To avoid data leakage, we choose to pre-train the mapping network on VIST, which is not revealed to CommonGen.

5 Result and Analysis

5.1 Main Results

We report few-shot open-ended text generation results with 1% of the training data for all the experiments discussed in this section.

Sentence Completion As shown in Table 2, StoryEndGen (#2) suffers from degeneration with the highest rep-*n* and the lowest diversity. Training with only 1% of the training data improves GPT2’s performance on all metrics (#3 vs. #1). Under the same few-shot setting, adding additional machine-generated images with our iNLG (#4) further alleviate model degeneration. The improvement on MAUVE also indicates that introducing visual input can aid GPT2 in generating text that is more similar to the human-written ones.

Story Generation As shown in Table 2, for the story generation task that requires the LM to compose longer text, we see the vanilla GPT2 without tuning suffering from more severe degeneration compared to rendering a sentence ending (#6 vs. #1). The two non-Transformer-based baselines (#7-#8) have worse performance compared to the models based on GPT-2 (#9-#11). Applying iNLG to GPT-2 leads to minor degeneration and has the best performance on all metrics (#11).

Concept-to-Text Table 4 shows that knowledge graph information may not be fully exploited under the few-shot setting (#2), while removing the information of relative positions between input concepts helps the LM write better sentences (#3). Introducing machine-generated images can improve the base LM’s performance on concept-to-text gener-

Task	Models	Coherence			Fluency			Informativeness		
		Win(%)	Tie(%)	Lose(%)	Win(%)	Tie(%)	Lose(%)	Win(%)	Tie(%)	Lose(%)
Sentence Completion	Ours vs. StoryEndGen	51.67	20.33	28.00	44.67	19.33	36.00	41.33	18.33	40.33
	Ours vs. GPT2 <i>no finetune</i>	51.00	22.67	26.33	45.00	22.33	32.67	41.00	21.00	38.00
	Ours vs. GPT2 <i>text-only finetune</i>	58.00	24.33	17.67	43.33	18.67	38.00	42.33	21.67	36.00
Story Generation	Ours vs. Action-Plan	51.00	24.67	24.33	54.67	16.33	29.00	52.00	15.00	33.00
	Ours vs. Plan-and-Write	45.33	25.67	29.00	53.00	16.67	30.33	54.67	17.00	28.33
	Ours vs. SimCTG	42.00	27.67	30.33	40.33	25.67	34.00	43.33	18.33	38.33
	Ours vs. GPT2 <i>no finetune</i>	43.33	24.33	32.33	43.67	20.33	36.00	44.67	19.00	36.33
	Ours vs. GPT2 <i>text-only finetune</i>	39.33	26.67	34.00	38.67	26.67	34.67	44.33	22.67	33.00

Table 3: Human evaluation results for the sentence completion task and the story generation task. The scores indicate the percentage of win, tie or lose when comparing our iNLG with the baseline models.

* Setting	B-4	M.	CIDEr	SPICE	BertS.
1 BART-base <i>text-only finetune</i>	20.72	25.47	114.49	24.58	59.76
2 +KG (Liu et al., 2021)	15.26	24.44	98.53	23.13	52.76
3 +Adapt (Ma et al., 2021)	23.11	25.96	123.44	25.14	61.53
4 +I&V (Wang et al., 2022a)	24.50	25.89	119.61	25.59	57.29
5 +iNLG	24.97	26.42	128.13	26.77	62.84

Table 4: Automatic metrics scores for few-shot concept-to-text generation on CommonGen with 1% of the training data. All listed models are implemented on BART-base. “+KG” adds knowledge graph, “+Adapt” applies model adaption, “+I&V” adds scene graph, and “+iNLG” introduces machine-generated images as input. B-4: BLEU-4; M.: METEOR; BertS.: BERTScore.

ation (#5 vs. #1). While both I&V and our iNLG involve machine “imagination”, we provide such information in different forms (scene graphs vs. images). Comparing #4 and #5, our iNLG outperforms I&V with BART-base as the base LM. This suggests that the additional information introduced by I&V and iNLG is complementary.

Human Evaluation Table 3 lists out human evaluation results on text completion and story generation. Our iNLG outperforms the compared baselines on all three criteria in the model-level head-to-head comparisons. This further verifies the effectiveness of our iNLG in generating fluent and informative text snippets that better align with the given context.

5.2 Performance Analysis

Source of Image We first perform an ablation study to understand how the source of visual information affects our iNLG framework. Specifically, we use retrieved/generated images from three sources: (1) the first returned result by Yahoo Image Search;¹⁰ (2) images rendered by VQGAN+CLIP (Crowson et al., 2022a);¹¹ (3) images

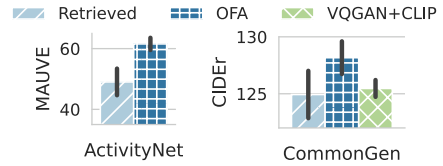


Figure 3: iNLG’s performance on CommonGen and ActivityNet with visual supervisions retrieved from the web or generated by machines. Scores are reported with error bars.

rendered by OFA (Wang et al., 2022b), with which we report the main results. As shown in Figure 3, the images generated by OFA or VQGAN+CLIP act as a more effective supervision than the retrieved images. Among the two text-to-image generators, OFA outperforms VQGAN+CLIP. This validates our motivation of introducing machine-generated images over retrieved ones to guide LM in performing open-ended text generation.

Mapping Network & Visual Prefix We discuss the effects of different types of mapping networks and various visual prefix lengths. Aside from the 8-layer Transformer we used in the main experiments, we also tried a simple Multi-Layer Perceptron (MLP) with two fully-connected layers. As shown in Figure 4, the Transformer-based mapping network outperforms MLP on all listed l . MLP has the best performance when visual prefix length $l = 15$, while the Transformer-based mapping network scores highest when $l = 20$.

Contrastive Training We examine the effect of the contrastive training objective on CommonGen, and the results are presented in Figure 5. We notice that introducing $\mathcal{L}_{\text{contrastive}}$ improves iNLG’s performance on 4 out of 5 listed few-shot setups, which suggests that our contrastive training objective generally can assist the LM in composing open-ended text snippets. One exception is in the extreme few-

¹⁰<https://images.search.yahoo.com/>

¹¹<https://github.com/nerdyrodent/VQGAN-CLIP>

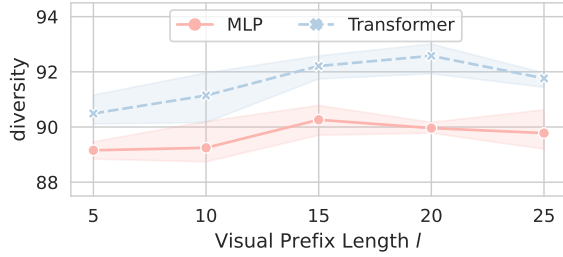


Figure 4: Performance of our iNLG on few-shot sentence completion with various visual prefix lengths and with MLP and Transformer as mapping network. Scores are reported with error bands.

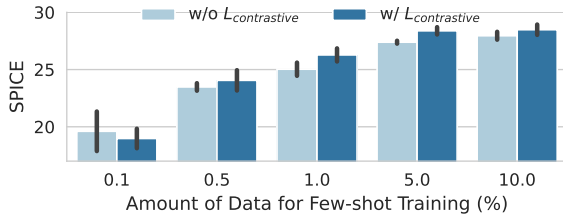


Figure 5: Performance of applying our iNLG on BART-base for few-shot concept-to-text with ablated training objective $\mathcal{L}_{\text{contrastive}}$ on various few-shot settings. Scores are reported with error bars.

shot setting with only 0.1% of training data, where the amount of data is insufficient to let the LM form a decent representation. In this case, enforcing the sentence representation to be similar to the visual supervision with $\mathcal{L}_{\text{contrastive}}$ might misguide the LM.

Model Weight Tuning Table 5 compares the influence of pre-training/tuning the weights of different modules of our iNLG. Generally speaking, tuning the weights during training outperforms freezing the weights, which applies to both the base LM and the mapping network. In addition, considering our few-show setup, pre-training the mapping network also helps our iNLG gain better performances. The best combination is applying the pre-trained mapping network, and tuning it together with the base LM on the few-shot downstream task.

Showcase Figure 6 provides two showcases on few-shot sentence completion and story generation to compare our iNLG with the GPT2-based baselines. We see SimCTG and GPT2 tuned with text-only corpus rendering repeated segments, either copying from the input context, or simply repeating themselves. In comparison, our iNLG has minor degeneration and writes coherent sentence ending

Tune LM	Pretrain Map.	Tune Map.	diversity \uparrow	MAUVE \uparrow
\times	\times	\times	15.52	0.47
\times	\times	\checkmark	78.20	33.79
\times	\checkmark	\times	27.06	1.83
\times	\checkmark	\checkmark	76.36	25.15
\checkmark	\times	\times	87.45	48.06
\checkmark	\times	\checkmark	88.68	51.81
\checkmark	\checkmark	\times	89.05	55.61
\checkmark	\checkmark	\checkmark	92.68	60.62

Table 5: Performance of our iNLG on few-shot sentence completion with ablated settings on whether to tune the LM, pretrain the mapping network (Pretrain Map.) and tune the mapping network (Tune Map.).

Context: Two girls are standing in a yard wearing cheerleading outfits. A girl...

Generated Image:

GPT2 (text-only)	is <u>standing in a yard</u> with a group of girls.
GPT2 +iNLG	is wearing a white bikini and blue shorts.

(a) Sentence Completion

Context: Barry at the Mall. Barry and his friends spent a day at the mall.

SimCTG	Barry was at the mall with his friends. They were all very excited to see him at the mall. <u>They all had a great time at the mall.</u> <u>They all had a great time at work.</u> <u>They all had a great time at school.</u>
GPT2 (text-only)	They went to the local mall and <u>bought a new car.</u> <u>They drove to the mall and bought a new car.</u> <u>They drove to the mall and bought a new car.</u> Barry's friends were very happy they <u>bought a new car.</u>
GPT2 +iNLG	They were swamped by the crowds. Barry was scared to go home. They tried to avoid the mall, but they were stopped by the people at the mall.

(b) Story Generation

Figure 6: Sentence ending and stories generated by GPT2-based methods tuned with 1% of the training data. *Repetitive contents* are underlined. The sentence ending and story written by our iNLG is coherent with the context, related to the machine-generated image, and has minor degeneration.

or story with more creative details in both tasks. More showcases are provided in the Appendix.

6 Conclusion

In this work, we propose iNLG, a framework that introduces machine-generated images to guide open-ended text generation. This endows the machines with the ability of creative visualization that human writers often demonstrate. We distill the vision information from the pre-trained multimodal models and further construct visual prefix to guide language models to perform text generation with the teacher forcing and the contrastive objective. Extensive experiments show the effectiveness of iNLG in open-ended text generation tasks, including text completion, story generation, and concept-to-text generation in few-shot settings.

Limitations

In this work, we use pre-trained multimodal models to visualize machine imagination. The machine-generated images may contain uncontrolled bias if any inductive bias exists from the pre-training data. Even though we do not witness such an issue in our study, this may be a potential factor that affects the quality of the generated text.

Moreover, in our current approach, the images are generated offline. In future work, one may explore combining text-to-image and image-to-text modules in an end-to-end manner, which may be more suitable for longer text generation that is not covered in this work.

Ethics Statement

We do not anticipate any major ethical concerns given that all the datasets and models used in this study have already been released in public. We reproduce baselines with the released code repository. We submit our code for experiments, and will make it public after the submission cycle.

For human evaluation, our study is approved for IRB exempt. The estimated hourly wage paid to MTurk annotators is \$10.

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A Appendix

A.1 Experiment Details

Text-to-Image Images are generated offline, and it takes ~ 1 min to render each image on both Titan RTX and A100.

Pretraining We pre-train the mapping network for GPT-2-base (Radford et al., 2019) on the MSCOCO (Lin et al., 2014) dataset with 414,113 (image, text) pairs for training. We pre-train the mapping network for BART-base (Lewis et al., 2020) on VIST (Huang et al., 2016) story-in-sequence subset, with 141,593 (image,text) pairs for training after excluding the images that the users have removed.

For each setting, we pre-train the mapping network for 5 epochs with a batch size of 128, learning rate of $2e-5$, weight decay of 0.01, and warmup steps of 5,000.

Few-Shot Training for Downstream Tasks Table 6 lists out the hyperparameters we used during few-show experiments on the three open-ended text generation tasks.

Hyperparameters	Concept-to-Text	Text Completion	Story Generation
Base LM	BART-base	GPT2-base	GPT2-base
Batch Size	8	8	8
Training Epoch	20	20	20
N_{no_contra}	4	10	15
λ	1.5	1	0.2
Learning Rate	$2e-5$	$2e-5$	$2e-5$
Weight Decay	0.01	0.01	0.01
Warmup Steps	400	400	400
Max Output Length	64	100	150
Num of Beam	10	10	10

Table 6: Hyperparameter settings for few-shot open-ended text generation.

Parameter Size Table 7 lists out the parameter size for the network modules used in our study.

Model	Parameter Size
BART-base	110M
GPT-2 base	117M
Mapping Network	42M
Projection Layer	1M

Table 7: Parameter size for the network modules used in our study.

Parameter Search We tried the learning rate in the following setting: $\{1e-5, 2e-5, 5e-5, 1e-4\}$, and tried the batch size in $\{4, 8, 16, 32\}$.

Instructions
Shortcuts
Which text snippet is more relevant to the given context?

Read the given context and the two piece of texts, determine **which text snippet is more relevant to the given context**. In other words, which snippet is more semantically consistent with the context, and follows the logic of the context more naturally?

Context: A man and a woman talk to the camera in a newscast setting. The scene transitions to various people training in gymnastics. Two women are interviewed on camera sequentially. the scene ...

Text 1: changes to a more elaborate song.

Text 2: in the yard starts his lawn mower.

Select an option

1 - Text 1 is more relevant 1
2 - Tie 2
3 - Text 2 is more relevant 3

Submit

Figure 7: A screenshot of the MTurk interface for our human evaluation on text coherency.

Environment & Run Time All experiments are conducted on NVIDIA A100. Table 8 lists out the execution time for the three open-ended text generation tasks with 1% of the training data.

	Text-only	+ iNLG
ActivityNet	50min	70min
ROCStories	70min	95min
CommonGen	40min	55min

Table 8: The average execution time for one single run (training + inference). Numbers reported on A100.

A.2 Human Evaluation

We invite MTurk¹² annotators to judge the quality of the generated text. Figure 7 shows the template we use for head-to-head comparison.

A.3 More Showcases

Figure 8 compares the images retrieved from Yahoo Image Search and the images generated by OFA (Wang et al., 2022b), which is the text-to-image generation model we used in this work.

Figure 9 and Figure 10 show more examples comparing the sentence ending / story generated by different models.

Context 1: One of the guys hits the ball over to the other side and they hit it back. Then on the other side of the beach there is a group of women also playing volleyball. They...



(a1) Retrieved Image



(b1) Generated Image

Context 2: A boy is talking to a camera. He goes into a bathroom and drinks a cup of mouthwash. He...



(a2) Retrieved Image



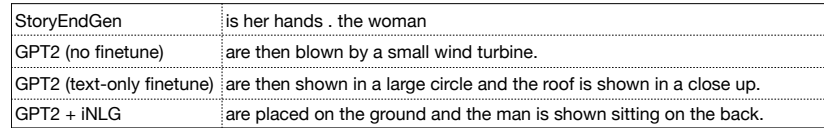
(b2) Generated Image

Figure 8: With the context as input, (a1)(a2) is the first returned image by the Yahoo image search engine,¹³ and (b1)(b2) is generated by the OFA (Wang et al., 2022b) model. The two input contexts are from the ActivityNet (Heilbron et al., 2015) subset in Hel-laSwag (Zellers et al., 2019).

¹²<https://www.mturk.com/>

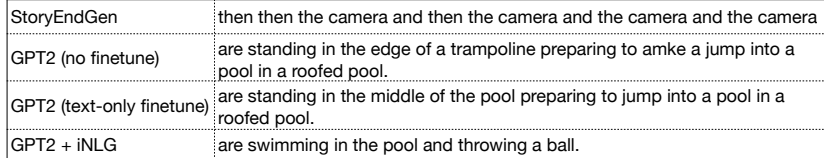
¹³Link to Yahoo image search: [link1](#), [link2](#)

Generated Image:



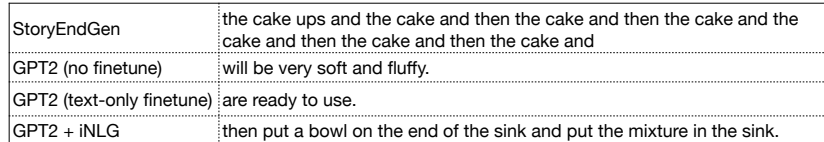
Context: Men are standing in the edge of a trampoline preparing to make a jump into a pool in a roofed pool. People...

Generated Image:



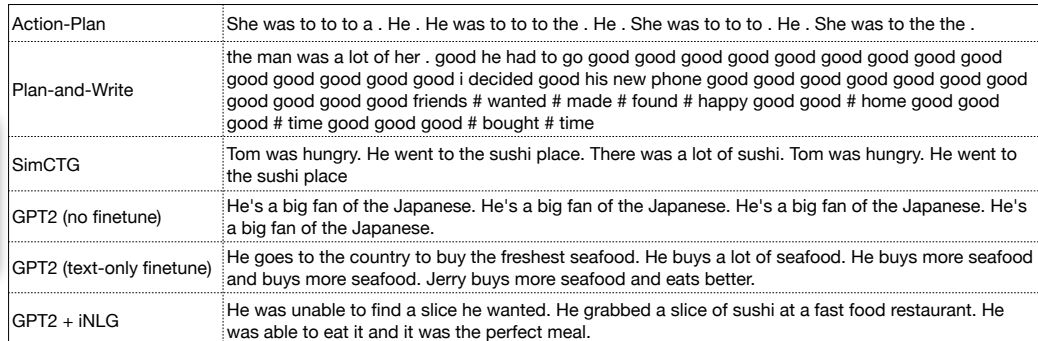
Context: They mix the eggs around a bowl and place butter and milk into another bowl and mix them all together. They...

Generated Image:



Context: Sushi. Jerry loves to eat food from other nations.

Generated Image:



Context: Hole in the House. Tim was putting away some paperwork in the attic.

Generated Image:

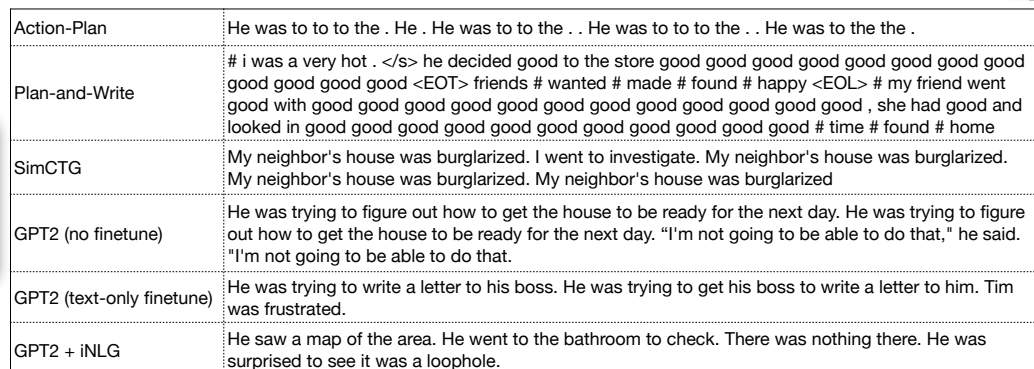


Figure 10: Comparisons on few-shot story generation performance on ROCStories.