Optional semester project report – text-to-image generation for multimodal large language models

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Abstract

Recent advances in multimodal large language models (MLLMs) deliver good performance on multimodal tasks, e.g, visual question answering, image/video captioning, retrieval, etc. At the same time, there has been a lot of progress in text-to-image generation thanks to the advancements in diffusion modeling, leading to many creative downstream use cases. To achieve such success, these diffusion models are trained on internet-scale data, and they have learned a lot of knowledge about the visual world and how visual concepts are usually described in natural language. In this project, we explore the possibility of obtain a MLLM that exploits the intrinsic knowledge of such diffusion models. For this purpose, we instantiate two architectures, with the first one using synthesized images to help MLLMs solve text-only tasks and the second one (still work in progress) bypassing the image generation step and directly enable a LLM to understand feature representations learned by Stable Diffusion. By conducting extensive experiments and ablation studies, despite some drawbacks, we obtain promising results, showing the potential of diffusion models as visual interpreters in the MLLM framework, especially when input images are not available.

1 Introduction

Recent advances in multimodal large language models (MLLMs) deliver good performance on multimodal tasks, e.g, visual question answering, image/video captioning, retrieval, etc. A notable example is GPT4-Vision (Achiam et al., 2023). At the same time, there has been a lot of progress in text-to-image generation thanks to the advancements in diffusion modeling, leading to many creative downstream use cases. A notable (closed-source) example is DALL·E 3 (Betker et al., 2023). To achieve such success, these diffusion models are trained on internet-scale data, and they have learned a lot of knowledge about the visual world and how visual concepts are usually described in natural language. In this project, we explore the possibility of obtain a MLLM that exploits the intrinsic knowledge of such diffusion models.

Concretely, we propose two architectures:

- Architecture 1 (Fig. 1a): Use an off-the-shelf diffusion model to generate an image from the input text-only task prompt, then feed both into an off-the-shelf MLLM to predict the text output.
- Architecture 2 (Fig. 1b): Use the diffusion model, e.g., Stable Diffusion (Rombach et al., 2022) as a visual encoder of the MLLM, bypassing the image generation. At the moment, this is work in progress, and we only train it as a regular MLLM that requires both image and text inputs to reason visually.

By conducting extensive experiments and ablation studies, despite some drawbacks, we obtain promising results, showing the potential of diffusion models as visual interpreters in the MLLM framework, especially when input images are not available.

2 Related work

Multimodal large language models. In the current era of large language models, there has been a recent resurgence of vision-language models (VLMs), especially image-to-text models. Different from a previous iteration of VLMs based on encoder-only language models (Lu et al., 2019, *inter alia*), the BLIP model series (Li et al., 2022a, 2023b; Dai et al., 2023) introduces the idea of aligning visual features, usually CLIP-based features (Radford et al., 2021), to the text token embedding space of a LLM via a multimodal projector module. This recipe turns out to be successful and thus adopted by many contemporary works (Huang

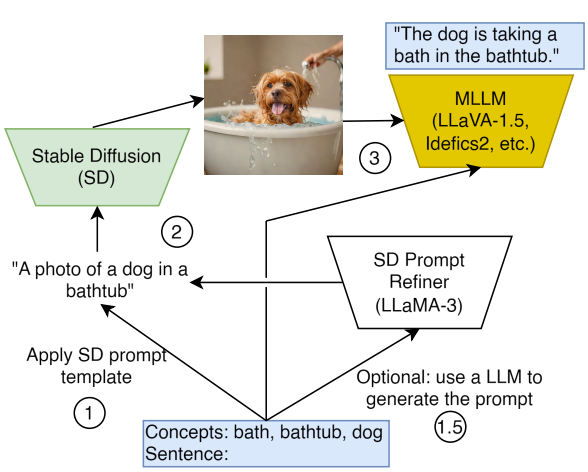
et al., 2023; Peng et al., 2024; Ye et al., 2023, 2024; Zhu et al., 2024; Liu et al., 2023b, 2024a). However, the main limitation of these methods is that they do not support more complex image-text configurations such as interleaved image-text sequences or multi-image inputs. The key idea to tackle this challenge is the inclusion of interleaved web-scale image-text data into the training data mix (Alayrac et al., 2022; Awadalla et al., 2023; Li et al., 2023a; Zhao et al., 2024; Laurençon et al., 2023, 2024; Sun et al., 2024a,b; Lin et al., 2024). These methods demonstrate that such a training strategy unlocks the MLLM's ability to perform multimodal in-context learning. Please refer to surveys (Wadekar et al., 2024; Caffagni et al., 2024; Bai et al., 2024; Yin et al., 2023; Bordes et al., 2024; Zhang et al., 2024a; Song et al., 2023) as well as ablation studies (Karamcheti et al., 2024; McKinzie et al., 2024; Lin et al., 2024) for a thorough understanding of this rapidly evolving field.

Visually-augmented natural language modeling. Similar to VLMs, one line of research focuses on enhancing language models with either generated or retrieved visual inputs, hoping to boost their performance on tasks such as natural language understanding (NLU), natural language generation (NLG), or machine translation (MT). iACE (Lu et al., 2022) trains a cross-modal encoder by distilling from pre-trained vision-language backbones, where images are generated by a VQGAN (Esser et al., 2021; Crowson et al., 2022). Meanwhile, Z-LaVI (Yang et al., 2022) implements a zero-shot pipeline by enhancing language models' predicted probabilities with CLIP-based (Radford et al., 2021) image-text similarity scores, where images are both retrieved via a search engine and generated by DALL·E (Ramesh et al., 2021). VaLM (Wang et al., 2023) and MORE (Cui et al., 2024) retrieve images, while LIVE (Tang et al., 2023b) uses Stable Diffusion (Rombach et al., 2022) to generate them. Both works fuse visual features with textual features deep within the language model decoder via cross-attention. Meanwhile, iNLG (Zhu et al., 2023) has a similar architecture to the MLLMs discussed above and introduces a contrastive loss to enforce similarity of the generated text to the visual features. Arguably, one drawback of these methods is the added time to generate or retrieve images. Thus, VAWI (Guo et al., 2023a) bypasses this step by directly using the CLIP (Radford et al., 2021) text features as a proxy to visual features. Similarly, Hagström and Johansson (2022) proposes different methods to adapt a VLM to a text-only input. Notably, all these methods use CLIP as the visual encoder. Meanwhile, in machine translation, visual inputs (either given or generated) are employed as extra context to enhance translation quality (Li et al., 2022b; Guo et al., 2023b, *inter alia*). Different from these methods, which all train from scratch the model's ability to understand images or side information, our pipeline utilizes pre-trained MLLMs with strong zero-shot capabilities, augmented by images synthesized by state-of-the-art text-to-image diffusion models (Podell et al., 2024; Sauer et al., 2023; Chen et al., 2024).

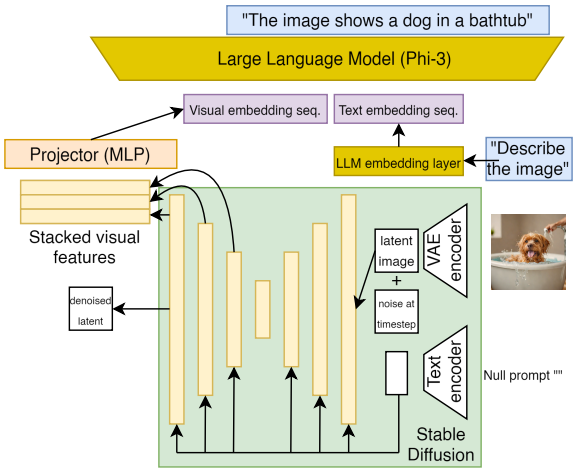
Using diffusion models for downstream tasks. Recent text-to-image diffusion models have been popular, notably open-source models such as Stable Diffusion (Rombach et al., 2022; Podell et al., 2024) which is based on the U-Net (Ronneberger et al., 2015) and Pixart-Σ (Chen et al., 2024) which is based on the Diffusion Transformer (Peebles and Xie, 2023). These models, with their rich internal representations, have boosted the usefulness of downstream applications such as image editing (Mokady et al., 2023; Luo et al., 2024, *inter alia*), image-to-image variation (Ramesh et al., 2022), as well as computer vision tasks such as segmentation (Xu et al., 2023; Zhao et al., 2023, *inter alia*) and semantic correspondence (Zhang et al., 2023; Tang et al., 2023a; Luo et al., 2023). Moreover, diffusion models have also been used as a "visual decoder" in MLLMs so that they can generate images with better prompt adherence (Sun et al., 2024b,a; Dong et al., 2024; Koh et al., 2024; Ge et al., 2024). On the other hand, one work (He et al., 2024) attempts to use Stable Diffusion (Rombach et al., 2022), more specifically its VAE (Esser et al., 2021), as the visual encoder. Inspired by these works, we propose a new model that uses the diffusion-based U-Net as the visual encoder in the LLaVA (Liu et al., 2023b) architecture.

3 Methodology

Problem statement. In this project, we examine whether modern LLMs, e.g., LLaMA-2 (Touvron et al., 2023), are able to perform better on text-only tasks such as multiple-choice question answering (MCQA) and natural language generation (NLG) when they are incorporated into a MLLM framework, e.g., LLaVA (Liu et al., 2023b). For this purpose, inspired by visually-augmented language



(a) Architecture 1: Our proposed pipeline for enhancing MLLMs on text-only tasks with synthetic image generation. In step 1, we extract a prompt for the diffusion model to generate an image (step 2), after which we feed both the synthesized image and the input task prompt into the MLLM (step 2).



(b) Archicture 2: Our proposed method to equip a LLM, Phi-3 (Abdin et al., 2024), with a T2I diffusion-based visual encoder, Stable Diffusion (Rombach et al., 2022). Our current MLLM architecture closely follows (Liu et al., 2024a) and (Karamcheti et al., 2024).

Figure 1: Our two instantiations of incorporating text-to-image diffusion models into the MLLM framework. The example input-output pair in both figures (in blue) is taken from the CommonGen dataset (Lin et al., 2020). The picture was generated using SDXL-Turbo (Sauer et al., 2023).

models (Tang et al., 2023b; Zhu et al., 2023), we investigate using MLLMs whose inputs are the input texts of the given textual task and synthetic images generated by diffusion-based models when prompted with the input text (e.g., the question of a MCQA sample).

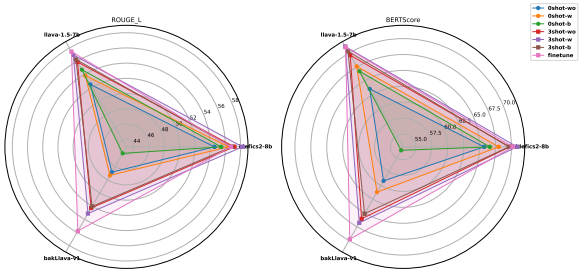
3.1 Preliminary: Multimodal LLMs

Contemporary MLLM architectures usually have three modules: a visual encoder, a multimodal projector, and a LLM decoder. The idea is to enable pre-trained LLMs to understand visual inputs such as images and videos encoded by pre-trained visual foundation models such as CLIP (Radford et al., 2021) or DINO (Oquab et al., 2024). The projector then projects visual features into the LLM space as embeddings of "visual tokens", to be prepended to the text token embeddings. This whole concatenated sequence is then fed into the LLM, which generates new text tokens autoregressively. The learning objective is usually the regular language modeling objective, i.e., the autoregressive factorization of the joint log-likelihood of the input sequence, conditioned on the visual embeddings.

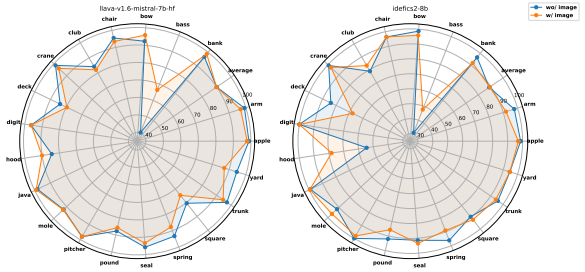
There are usually two stages when training a MLLM. In the first stage, called the pre-training stage or alignment stage, the MLLM learns to align visual features with text features. Here, only the projector is trainable. This stage often uses paired text-image data, such as captions (e.g., Sharma et al., 2018). In the second stage, called the fine-tuning stage or visual instruction tuning (Liu et al., 2023b), both the projector and the LLM are fine-tuned on multimodal instruction data such as visual question answering (e.g., Goyal et al., 2017).

3.2 Preliminary: Latent diffusion models

A text-to-image (T2I) diffusion model generates an image by iteratively denoising a noisy image over many timesteps. In this project, we only consider diffusion models that operate in a latent space, e.g., Stable Diffusion (Rombach et al., 2022) (SD) instead of the pixel space (e.g., Saharia et al., 2022). A T2I diffusion model has three components: a text encoder that encodes the user-provided text prompt, a VQGAN-based VAE (Esser et al., 2021) that encodes and decodes pixels into a latent space, and a U-Net (Ronneberger et al., 2015) or Diffusion Transformer (DiT) (Peebles and Xie, 2023) to predict the noise applied to the input (latent) image. During inference, the generation process begins with a random vector, which is then iteratively denoised over multiple timesteps, guided by the encoded text embeddings. Such textual conditioning is enabled by cross-attention layers in the U-Net or adaptive layer norm in the DiT (Peebles and Xie, 2023). In this project, we synthesize images with SDXL-Turbo (Sauer et al., 2023), a model distilled from SDXL (Podell et al., 2024) and generates an image in only a few timesteps.



(a) CommonGen results. `wo`: without image, `w`: with image; `b`: we use a constant black image as an ablation; `finetune`: model is fine-tuned on the whole train split.



(b) F1 scores across different words (and the macro-average). Using synthetic images helps for some words but hurts for other words, resulting in an unchanged average score.

Figure 2: Results for CommonGen and CoarseWSD-20. For CommonGen, synthetic images help a lot under the zero-shot setting, whereas they do not help much under the 3-shot setting. On the other hand, fine-tuning does not help much compared to 3-shot prompting; it only teaches the model how to do the task.

3.3 MLLM with synthetic images

As text-only tasks do not provide images in their datasets, we have two intuitive ways to evaluate MLLMs on these tasks. The first approach is to simply discard the visual encoder and the multimodal projector and only use the LLM part of the MLLM to process the textual inputs. This is possible since this module is usually just a fine-tuned version of the base LLM, as discussed above. Alternatively, we can attempt to "imagine" an image from the textual input and feed both into the MLLM.

To do this, we follow iNLG (Zhu et al., 2023) and use diffusion models (Sauer et al., 2023; Chen et al., 2024) to generate images with the prompt being the textual input of the text-only task (e.g., the question of the MCQA or the context of the NLG task). The pipeline, illustrated as Architecture 1 in Fig. 1a, consists of the following three steps:

Step 1: From the input task (e.g., MCQA), we extract a prompt for the T2I diffusion model. This process can be automatic (e.g., use as the prompt the question of a multiple-choice QA sample), or assisted by a LLM (AI@Meta, 2024), where we use a manual few-shot instruction to teach it how to generate/refine such prompts.

Step 2: Feed the extracted prompt to a T2I diffusion model to generate an image.

Step 3: Feed the original input task prompt (e.g., the concatenated question and possible MCQA options) and the synthesized image to the MLLM to generate textual outputs (e.g., the predicted answer).

3.4 MLLM with a SD-based visual encoder

A natural progression of the above approach is to bypass the image generation step and directly use features extracted from the diffusion model. Inspired by He et al. (2024), we replace the CLIP ViT commonly used in most contemporary MLLMs with the U-Net from Stable Diffusion v1.5 (Rombach et al., 2022) (SD1.5). More specifically, we follow Zhang et al. (2023, 2024b) and use the ResNet (He et al., 2016) output features of layers 2, 5, and 8 (out of 12 layers) from the upsampling blocks of the U-Net. Fig. 1b demonstrates our method, Architecture 2. Next, we explain more about our design choices.

In this project, we use the LLaVA-1.5 strategy (Liu et al., 2023b, 2024a), as implemented by Karamcheti et al. (2024). The visual encoder is usually the CLIP Vision Transformer (ViT) (Radford et al., 2021; Dosovitskiy et al., 2021), which embeds images into fixed-resolution visual patches (usually with a resolution of 16^2) during its pretraining. A multimodal projector then projects each patch embedding into the LLM embedding space. The projected visual sequence is then directly prepended to the sequence of text token embeddings and subsequently fed into the LLM for autoregressive sequence modeling. Although a ViT can be modified so that it can input and output at any resolution (Dehghani et al., 2023), increasing the resolution of the input images usually lead to more patches, meaning a longer visual sequence for the LLM. Provided that no resampling mechanism is used, this can boost the performance of the MLLM at the expense of longer training and inference time (Pantazopoulos et al., 2024; Cha et al., 2024) due to the quadratic complexity of the attention mechanism.

Back to SD1.5, its native input/output resolution is 512^2, whereas the U-Net features have differ-

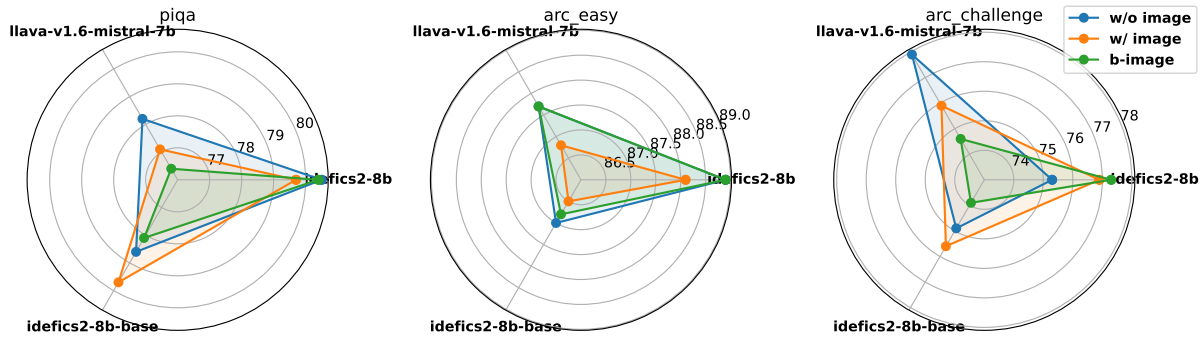


Figure 3: Results on PIQA, AI2 ARC showcasing the impact of using synthetic images. Zero-shot. Black image means we use a constant black image instead of synthesizing it.

ent spatial resolutions (8^2, 16^2, and 32^2 for layers 2, 5, and 8 respectively). In contrast to works that use a projector that resamples the visual sequence to a short length, we simply follow LLaVA-1.5 (Liu et al., 2024a) and use a multilayer perceptron (MLP), which maintains the length of the visual tokens. Thus, at the time of writing this manuscript, we opt to resize each U-Net feature to a fixed size (e.g., 16^2) using naive bilinear interpolation (we leave the method of adaptive average pooling (Pantazopoulos et al., 2024) for future work), then stack them along the channel dimension to create the output visual sequence, which is subsequently fed into the multimodal projector as described above.

In addition, inspired by Karamcheti et al. (2024); Tong et al. (2024); Kar et al. (2024), we explore combining visual features from different visual encoders: SDv1.5 (Rombach et al., 2022), SigLIP (Zhai et al., 2023), and DINOv2 (Oquab et al., 2024). To create an ensemble of features, we currently follow Karamcheti et al. (2024) and simply feed the image to each encoder separately and stack the resulting visual patch representations in the channel dimension. The rest of the MLLM pipeline proceeds as described above.

Using SD as a visual encoder is non-trivial as it was originally trained to denoise images over multiple timesteps, guided by a text prompt (Ho and Salimans, 2021). However, as proof-of-concept, we opt to ablate and simply extract SD features by running only one denoising step with the timestep being 0, meaning there is no added noise, please see Fig. 1b. We also do not feed text prompts into SD and instead use a null prompt (empty string), following the computer vision literature about using diffusion features on real images (Luo et al., 2024; Tian et al., 2024). We leave to future work exploration of more complex diffusion feature extraction strategies: running the denoising process over many timesteps (even starting from random noise – no need for images), ablating over U-Net layer features, using text prompts, or using better diffusion models such as Stable Diffusion 3 (Esser et al., 2024).

4 Experiments

4.1 MLLM with synthetic images

Tasks. We evaluate Architecture 1, MLLM with synthesized images (Fig. 1a), on two text-only tasks [1]. The first task is multiple-choice question answering (MCQA) including the following datasets: PIQA (Bisk et al., 2020), which is about physical commonsense, ARC (Clark et al., 2018), which is about grade-school science, and CoarseWSD-20 (Loureiro et al., 2021), which disambiguates ambiguous words (e.g., apple or Apple) by choosing the correct meaning (sense) in a given context. The second task is text generation with CommonGen (Lin et al., 2020), which generates a sentence given concepts.

Metrics. For MCQA, we use the F1 score to account for class imbalance. For CommonGen, we follow previous work (Wang et al., 2022; Zhu et al., 2023; Tang et al., 2023b; Guo et al., 2023a; Cui et al., 2024) and use BLEU-4 (Papineni et al., 2002) which computes precision in n-gram overlap between predictions and references, ROUGE-L (Lin, 2004) which focuses on recall, METEOR (Banerjee and Lavie, 2005) which combines both precision and recall, CIDEr (Vedantam et al., 2015) which evaluates consensus based on word frequency, SPICE (Anderson et al., 2016) which

[1] Our code is hosted at https://github.com/sonalexle/vlm-viz/

Method	k-shot?	Image?	B-4	R-L	Met.	CIDEr	SPICE	BertS.
MORE-OPT-2.7b (Cui et al., 2024)	FT	✓	32.8	57.1	32.1	17.0	32.9	-
I&V T5-large (Wang et al., 2022)	FT	✓	**40.6**	-	-	17.7	31.3	-
LIVE-T5 (Tang et al., 2023b)	FT	✓	27.9	-	-	15.8	31.4	-
iNLG-T5-large (Zhu et al., 2023)	FT	✓	34.5	-	**33.9**	17.8	**35.5**	72.7
VAWI-SBS-T5-3b (Guo et al., 2023a)	FT	✓	37.5	**59.9**	33.4	**18.3**	34.7	-
llava-1.5-7b (Liu et al., 2024a)	FT	✓	32.5	57.5	33.4	17.1	33.9	71.1
Mistral-7B-v0.1 (Jiang et al., 2023)	0	✗	21.2	49.8	26.6	12.2	25.6	57.4
llava-1.5-7b	0	✗	26.8	52.5	29.8	14.5	28.1	63.5
llava-1.5-7b	0	✓	26.9	53.8	30.4	14.7	29.9	67.6
idefics2-8b-base (Laurençon et al., 2024)	0	✗	30.0	54.3	29.7	15.2	28.4	65.1
idefics2-8b-base	0	✓	31.7	56.2	30.8	15.9	30.4	68.4
gpt-3.5-turbo* (Ouyang et al., 2022)	3	✗	28.9	53.2	31.1	15.9	28.9	-
Mistral-7B-v0.1	3	✗	36.2	58.9	32.3	17.5	32.0	72.5
llava-1.5-7b	3	✗	31.1	55.9	32.1	16.1	30.9	69.6
llava-1.5-7b	3	✓	32.4	57.0	32.6	16.8	32.4	71.2
idefics2-8b-base	3	✗	36.8	59.0	32.7	17.8	33.5	72.6
idefics2-8b-base	3	✓	37.2	59.3	32.9	18.0	33.5	**72.8**

Table 1: CommonGen results. **Bold** is highest, underline is second highest. B-4 is BLEU-4; R-L is ROUGE-L; Met. is METEOR; BertS. is BERTScore. FT means the model was fine-tuned on either the CommonGen train split or some external dataset used in some previous work. ✓ means we feed the generated image into the model, and vice versa for ✗. *: evaluated by Cui et al. (2024).

measures semantic content via scene graphs, and BERTScore (Zhang et al., 2020) uses BERT embeddings (Devlin et al., 2019) to compute semantic (cosine) similarity between words in predicted and reference sentences.

Models. For synthesizing images, we use Stable Diffusion XL (SDXL) Turbo (Sauer et al., 2023), a state-of-the-art open-source diffusion model that generates a high-quality image in just one step. We also experimented with Pixart-Σ (Chen et al., 2024) but the generations were not high-quality. For extracting prompts for T2I, we use LLaMA-3 (Touvron et al., 2023). For MLLMs, we use a variety of models: LLaVA-1.5 (Liu et al., 2024a) (Vicuna-7b (Zheng et al., 2023) backbone), LLaVA-NeXT (Liu et al., 2024b) (Mistral-7b (Jiang et al., 2023) backbone, multi-crop strategy), BakLLaVA [2] (Mistral-7b backbone, LLaVA-1 recipe (Liu et al., 2023b)), and Idefics-2 (Laurençon et al., 2024) (Mistral-7b backbone, interleaved data pre-training, better modeling strategy). Laurençon et al. (2024) provide two checkpoints, Idefics-8b-base and Idefics-8b, where the former is a pre-trained only checkpoint (stage 1 as described in Section 3.1), instead of visual instruction tuning as in the case of the latter (meaning it was trained under both stages 1 and 2).

Image generation strategy. As mentioned above, we use LLaMA-3 (AI@Meta, 2024) to generate SD prompts (SD Prompt Refiner in Fig. 1a), which are then used by SDXL Turbo to generate images. We do these two steps offline before running the benchmarks. For PIQA and ARC, we manually construct a few-shot in-context learning (ICL) instruction prompt for LLaMA-2, where we use examples from the train split as the context. For CommonGen, we use as context the example concepts [3] (the prompt template) given by (Clark et al., 2018). Then, we manually all in-context SD prompt exemplars given each context. Note that this prompt generation step is not necessary; however, the generated images would be of lower quality as current open-source diffusion models' prompt adherence skill is limited (Hu et al., 2024).

Implementation details. Regarding prompt templates, we experimented with using chat templates (i.e., user, assistant roles) and found that not using a template improves the results; thus, we only report results without chat templates. For MCQA, we perform 0-shot inference and format the prompt as "`Question: Options: (A) (B) etc. Answer: (`" (among other strings) and have the model generate a letter (prompt inspired by Li et al. (2024)). For CommonGen, we either fine-tune our models on the full train split, or we conduct 0-shot and

[2] https://github.com/SkunkworksAI/BakLLaVA

[3] https://huggingface.co/datasets/allenai/commongen_lite

Visual encoder	AI2D	GQA	POPE	Tally-QA	Text-VQA	Vizwiz	VQAv2	VSR	Avg.
sd1.5	57.3	58.2	85.4	56.4	12.2	26.6	70.6	61.5	53.5
dino	58.4	61.0	86.3	60.7	12.8	29.1	72.4	59.3	55.0
dinosiglip	61.5	62.3	86.6	62.1	38.1	38.8	76.7	**67.0**	61.6
siglipsd1.5	**61.9**	61.7	86.2	65.3	40.7	39.0	**77.1**	66.4	62.3
siglip	61.8	62.3	85.7	64.9	**41.9**	**41.8**	76.8	63.7	**62.4**
dinosiglipsd1.5	61.2	**62.4**	**87.3**	**66.0**	38.3	39.8	76.9	66.9	**62.4**

Table 2: The LLM decoder is always Phi-3. **Bolded** are best, underlined are second-best. Although the difference between the scores are tiny, we see that combining SD with at least SigLIP provides the best results. Note that results for VQAv2 and TallyQA are obtained from a 16K random subsample of the original splits. All displayed scores are accuracy scores as computed by official evaluation code.

3-shot inference (fixed in-context examples). Under the latter scenario, because these models were instruction-tuned, they often generate extra content besides the requested sentence, hence we apply a post-processing step to automatically extract the first sentence of the generated text. For CommonGen fine-tuning, the train split has roughly 65K samples; we use 1 epoch with a batch size of 32. Whenever we provide images as input, we modify the prompt to explicitly instruct the model to "observe" the image. As an ablation, we follow Hagström and Johansson (2022) and use a constant black image instead of synthesized ones. For all settings where synthetic images are provided to the model, only one image is provided per text input, even when 3-shot prompting is used.

CommonGen results. Results for CommonGen are shown in Fig. 2a and Table 1. Synthesizing images helps especially in the 0-shot case as it gives the model more idea on what kind of sentence to generate – we can think of the desired output as a kind of caption to the synthetic image. On the other hand, when we use three shots, generated images do not seem to help much. This might be due to the fact that the in-context examples might already be sufficient teach the model how to do the task, and thus it does not need to use the synthesized image. On the other hand, using a black image usually hurts the performance, as it might distract the model from actually performing the task, given that the LLM sees the image as a sequence of visual tokens of non-trivial length. Another observation from Table 1 is the difference in 0-shot text-only performance between Idefics2-8b-base and its LLM base model Mistral-7b-v0.1. Note that both models did not undergo any instruction tuning during their construction, although Idefics2's LLM module were LoRA-tuned (Hu et al., 2022) during its pre-training stage (Laurençon et al., 2024). This might suggest a transfer of visual knowledge to the LLM decoder.

CoarseWSD-20 results. CoarseWSD-20 results are shown in Fig. 2b. Here, we observe that synthetic images can help distinguish senses of some words, but it might be a distraction if the word is already easy enough. Thus, the average F1 score is almost unchanged.

PIQA and ARC results. PIQA and ARC results are displayed in Fig. 3. Again, these results not definitive and do not seem to have any pattern, besides the fact that they are model- and data-dependent. One possible explanation is that these tasks, although each sentence of the input prompt might be highly visualizable as the mentioned subjects are usually common nouns, answering the questions do not require visual knowledge and instead requires complex reasoning. This is in contrast to CommonGen and CoarseWSD-20, where the task inputs are usually easier to visualize or "imagine" (concepts for the former, descriptive context for the latter). We leave to future work the quantification of "imageability" of texts (Doostmohammadi and Kuhlmann, 2022; Kastner et al., 2021; Wu and Smith, 2023; Bird et al., 2001). Previous work on visually-augmented NLP has also explored this concept – they generate or retrieve images only when the input is highly visual (Tang et al., 2023b; Guo et al., 2023a), which is estimated by ad-hoc methods such as CLIPScore (Hessel et al., 2021).

4.2 MLLM with SD-based visual encoder

Tasks and metrics. Currently, we use the framework and implementation by Karamcheti et al.

(2024) to train our models. They propose an evaluation suite of multimodal tasks, from which we use AI2D (Kembhavi et al., 2016), GQA (Hudson and Manning, 2019), POPE (Li et al., 2023c), Tally-QA (Acharya et al., 2019), Text-VQA (Singh et al., 2019), Vizwiz (Bigham et al., 2010), VQA-v2 (Goyal et al., 2017), and VSR (Liu et al., 2023a). We also use (Karamcheti et al., 2024)'s implementation of the benchmarks to evaluate our models, where for Tally-QA and VQA-v2 we test on a 16K random subset (all other datasets have around 16K samples or fewer). These tasks are formulated as visual QA, with the official metric being the accuracy score as computed by the official codebases (also provided [4] by Karamcheti et al. (2024)).

Implementation details. As mentioned earlier in Section 3.4, we currently only use the most basic setup to reduce the degree of complexity of our implementation: SDv1.5 U-Net (Rombach et al., 2022) (extracting features from upsampling ResNet output layers 2, 5, 8, empty string, 1-step denoising with no added noise), input resolution 512^2 for SD and 224^2 for DINOv2 (Oquab et al., 2024) and SigLIP (Zhai et al., 2023), visual features always concatenated in the channel dimension (the spatial dimensions all resized to 224^2 using bilinear interpolation), MLP multimodal projector, Phi-3 (Abdin et al., 2024) as the LLM decoder, visual instruction-tuning only (Karamcheti et al., 2024) (the first stage, as mentioned above, is skipped) on the LLaVA-1.5 visual instruction dataset (Liu et al., 2024a). We leave to future work more complex modeling strategies.

Results. The full results can be found in Table 2. Although the SD encoder by itself is not competitive, ensembling it with SigLIP (Zhai et al., 2023) gives promising results. One explanation is that SD features, similar to DINO features, are not aligned with the language space unlike SigLIP features. This is because of their pre-training objectives: denoising diffisuion for SDv1.5, self-supervised learning for DINOv2, and contrastive image-text matching for SigLIP. Despite this naive feature fusion strategy, we observe non-trivial improvements given that each dataset has at least 4K samples. This is thanks to the complementary strengths of each visual encoder (Karamcheti et al., 2024; Tong et al., 2024; Kar et al., 2024): SD is good at spatial and depth understanding (Zhang et al., 2023); DINOv2 is good at discriminative features and semantics (Oquab et al., 2024); and SigLIP is good at vision-text alignment and it understands many concepts (Zhai et al., 2023).

[4] https://github.com/sonalexle/prismatic-vlms

5 Conclusion

In this project, we propose two architectures for MLLMs to exploit the knowledge learned by text-to-image (T2I) diffusion models. In the first architecture, we use T2I generation to directly synthesize images given the input text-only task, and obtained promising results on tasks that are more "visual", although the improvements are small compared to text-only baselines. In the second architecture, we directly replace the visual encoder module in the usual MLLM recipe with the U-Net (Ronneberger et al., 2015) of Stable Diffusion (Rombach et al., 2022). Although the results are not state-of-the-art, we design the architecture with minimal complexity, yet we already observe promising results, suggesting room for improvement.

As future work, we plan to evaluate our architecture 2 on text-only tasks that we evaluated on architecture 1 in this report. We also plan to investigate the concept of imageability (Doostmohammadi and Kuhlmann, 2022; Kastner et al., 2021; Wu and Smith, 2023; Bird et al., 2001), to understand when and if a diffusion model's visual "imaginations" help for texts that are highly "imageable". In addition, we plan to improve architecture 2 itself by exploring more complex modeling decisions, including but not limited to: multiple-step denoising to obtain features from different timesteps (non-trivial to possibly combine them), feeding text prompts to the diffusion-based visual encoder, and do not use images at all and only fine-tune the projector and LLM decoder on diffusion features "imagined" from the text prompt.

Furthermore, we plan to implement more complex multimodal projector architectures (e.g., Kar et al., 2024) to aggregate strengths from diffusion visual branches while maintain high visual fidelity and faithfulness. One idea could be to combine the spatially smaller but semantically stronger features of SigLIP (Zhai et al., 2023) with diffusion's spatially larger but semantically weaker features via feature pyramid network-like architecture (Lin et al., 2017) that aims to imbue larger feature maps with semantics from smaller feature maps. This idea has been used in the diffusion literature (Zhao et al., 2023; Xu et al., 2023).

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