ImagenHub: Standardizing the evaluation of conditional image generation models

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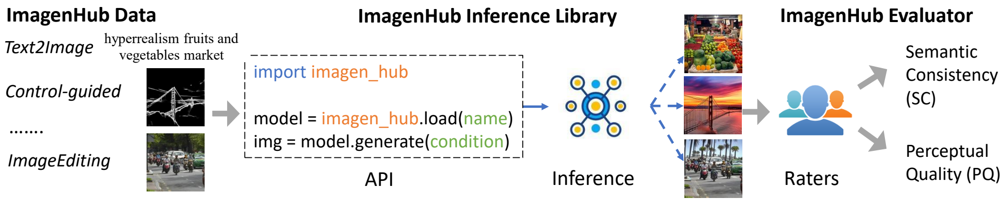
https://tiger-ai-lab.github.io/ImagenHub/

Abstract

Recently, a myriad of conditional image generation and editing models have been developed to serve different downstream tasks, including text-to-image generation, text-guided image editing, subject-driven image generation, control-guided image generation, etc. However, we observe huge inconsistencies in experimental conditions: datasets, inference, and evaluation metrics – render fair comparisons difficult. This paper proposes ImagenHub, which is a one-stop library to standardize the inference and evaluation of all the conditional image generation models. Firstly, we define seven prominent tasks and curate high-quality evaluation datasets for them. Secondly, we built a unified inference pipeline to ensure fair comparison. Thirdly, we design two human evaluation scores, i.e. Semantic Consistency and Perceptual Quality, along with comprehensive guidelines to evaluate generated images. We train expert raters to evaluate the model outputs based on the proposed metrics. Our human evaluation achieves a high inter-worker agreement of Krippendorff's alpha on 76% models with a value higher than 0.4. We comprehensively evaluated a total of around 30 models and observed three key takeaways: (1) the existing models' performance is generally unsatisfying except for Text-guided Image Generation and Subject-driven Image Generation, with 74% models achieving an overall score lower than 0.5. (2) we examined the claims from published papers and found 83% of them hold with a few exceptions. (3) None of the existing automatic metrics has a Spearman's correlation higher than 0.2 except subject-driven image generation. Moving forward, we will continue our efforts to evaluate newly published models and update our leaderboard to keep track of the progress in conditional image generation.

1 Introduction



```
import imagen_hub

model = imagen_hub.load(name)
img = model.generate(condition)
```

Figure 1: The overview of ImagenHub framework, which consists of the newly curated ImagenHub dataset, ImagenHub library, and ImagenHub evaluation platform and standard.

With the recent development of diffusion models, image generation has quickly become one of the most popular research areas in AI. To enable controllability in the image generation process, a myriad of conditional image generation models have been proposed in the past year. Diverse set of conditions have been attempted to steer the diffusion process. One of the most popular tasks is text-guided image generation (Ramesh et al., 2022; Rombach et al., 2022; Saharia et al., 2022), which aims to ground on a text prompt to generate the corresponding image. Besides that, there are also subject-conditioned image generation (Gal et al., 2022; Ruiz et al., 2023), text-guided image editing (Brooks et al., 2023), multi-subject-conditioned image generation (Kumari et al., 2023), style-guided image generation (Sohn et al., 2023), etc. These different tasks aim to serve different types of downstream applications by enabling subject-level, background-level, style-level controls. The field is evolving at an unprecedented pace and lots of improvements have been reported in the published papers. However, one glaring issue we observed is the published work are highly inconsistent in their experimental setups. To summarize, the inconsistencies mainly come from three aspects, namely dataset, inference and evaluation:

- **Dataset**: The existing work curated their own evaluation dataset, which makes the comparison of different models totally incomparable.
- **Inference**: Some work requires heavy hyper-parameter tuning and prompt engineering to achieve reasonable performance, which makes the model less robust. Due the tuning effort on different models differe significantly, their comaprison could become unfair.
- **Evaluation**: The existing work used different human evaluation protocols and guidelines. This inconsistency renders it impossible to compare human evaluation scores across different methods. Moreover, some of the work either employs a single rater or does not report inter-worker agreement. Thus, the reported results might not be comparable across different papers.

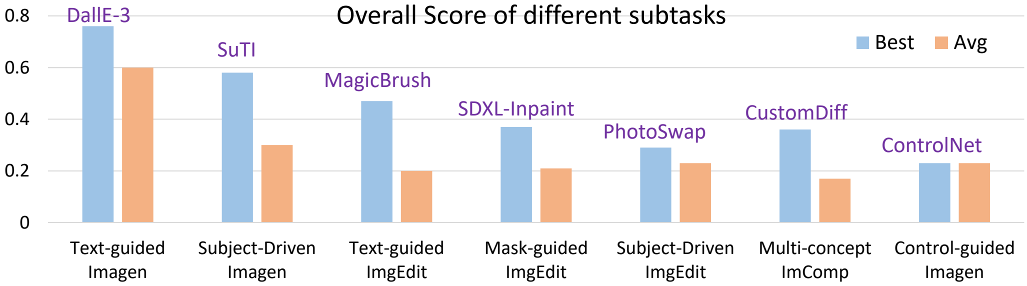


Figure 2: The best and the average model performance in each task

These three inconsistencies make it nearly impossible to track the real progress in the field of the conditional image generation. Such an issue could greatly hinder the development of this field. The desiderata is to build a centralized effort to fairly evaluate every model. More importantly, this effort needs to be continuous to keep up with the evolvement of the field. Our paper aims to serve this purpose to standardize the serving and evaluation of all open-source conditional image generation models. More specifically, ImagenHub consists of the modules listed in Figure 1.

ImagenHub Dataset. We surveyed the existing public evaluation sets for all the generation tasks and then picked diverse instances from them to build our ImagenHub dataset. ImagenHub dataset consists of 7 subsets, each with 100-200 instances. This dataset aims at standardizing the evaluation input to ensure fair comparison for different models.

ImagenHub Inference Library. We built a ImagenHub library[1] to evaluate all the conditional image generation models. We ported the highly dispersed codebase from the existing works and then standardized them into a unified format. During inference, we fixed the hyper-parameters and the prompt format to prevent per-instance prompt or hyper-parameter tuning, which makes the inference of different models fair and reproducible. The library is designed to be easily extendable. Our Appendix A.7, A.8, and A.9 show how a third party and researchers can benefit from our work.

ImagenHub Evaluator. We explored different human evaluation metrics and iterated over different versions of the rating guidelines to improve the inter-rater agreement. We settled on two three-valued rating metrics 'Semantic Consistency' and 'Perceptual Quality' to achieve generally high inter-worker agreement measured by Fleiss Kappa (Fleiss & Cohen, 1973) and Krippendorff's Alpha (Krippendorff, 2011). We designed a rating standard to achieve several benefits: (1) Our rating guide is an unambiguous checklist table such that the rater can rate the image with ease. (2) The

[1] it's similar to Huggingface libraries (Wolf et al., 2019; von Platen et al., 2022)

designed rating guideline is unified on every task type. (3) Sustainability. Since each model is rated individually, previous evaluation results can be reused when new models are added.

We demonstrate our evaluation results in Figure 2, where we show the overall score of the best-performing model and the medium-performing model. Based on our evaluation results in section 5, we made some general observations:

- The existing models' performance is generally unsatisfying except for Text-guided Image Generation and Subject-driven Image Generation.
- We found that evaluation results from the published papers are generally consistent with our evaluation. 83% of the published result ranking is consistent with our ranking.
- Automatic evaluation metrics do not correlate well with human preference well except subject-driven image generation. The correlation scores are lower than 0.2.

2 The problem of Conditional Image Generation

The goal of conditional image generation is to predict an RGB image $y \in \mathcal{R}^{3\times H\times W} : \mathcal{Y}$, where H and W are the height and width of the image. The prediction of the target image is given a set of input conditions $X = [c_1, c_2, \cdots]$, where $X \in \mathcal{X}$, where C_i denotes the i-th condition. In the problem, we aim at learning a prediction function $f : \mathcal{X} \rightarrow \mathcal{Y}$ with deep learning models. Here we mainly consider f parameterized with diffusion models. Here we list a set of tasks we consider in Figure 3, where c_i can be represented as text prompt, image mask, subject image, source image, background image, control signal, etc.

Task Definition. We formally define the tasks we consider as follows:

- Text-guided Image Generation: $y = f(p)$, where p is a text prompt describing a scene. The goal is to generate an image consistent with the text description.
- Mask-guided Image Editing: $y = f(p, I_{\text{mask}}, I_{\text{src}})$, where I_{mask} is a binarized masked image, and I_{src} is a source image. The goal is to modify given I_{src} in the masked region according to p.
- Text-guided Image Editing: $y = f(p, I_{\text{src}})$. It's similar to Mask-guided Image Editing except that there is no mask being provided, the model needs to figure out the region automatically.
- Subject-driven Image Generation: $y = f(S, p)$, where S is a set of images regarding a specific subject, which normally ranges from 3-5. The goal is to generate an image according to p regarding the subject S.
- Subject-driven Image Editing: $y = f(S, p, I_{\text{src}})$, where I_{src} is a source image and S is the subject reference. The goal is to replace the subject in I_{src} with the given subject S.
- Multi-concept Image Composition: $y = f(S_1, S_2, p, I_{\text{src}})$, where S_1 and S_2 are two sets of concept images. The goal is to compose them together to generate a new image according to the text description p.
- Control-guided Image Generation: $y = f(I_{\text{control}}, p)$, where I_{control} is the control signal like depth map, canny edge, bounding box, etc. The goal is to generate an image following the low-level visual cues.

3 Related Work

Multimodal Conditional Image Synthesis. Recent works in multimodal conditional image synthesis often rely on pre-trained vision-language models such as CLIP (Radford et al., 2021) and pre-trained large diffusion models like Stable Diffusion (Rombach et al., 2022). CLIP bridges the gap between textual descriptions and visual content, while Stable Diffusion is a latent diffusion model trained on a massive dataset. CLIP and Stable Diffusion are now widely used as core components in applications such as text-to-image generation, text-guided image editing (Patashnik et al., 2021; Meng et al., 2021; Couairon et al., 2022; Mokady et al., 2022; Zhang et al., 2023), and mask-guided image editing (Avrahami et al., 2022; Nichol et al., 2022). Another interesting research direction is image subject personalization with a few or even one image of the subject. Textual Inversion (Gal et al., 2022) optimizes a text token vector to represent the subject, while DreamBooth (Ruiz et al., 2023) finetunes the Stable Diffusion model to learn the new subject concept efficiently. These works foster research in potential applications like subject-driven image generation and editing (Li et al., 2023a;b; Gu et al., 2023), and even multi-concept image compositions (Kumari et al., 2023). To explore more control conditions, ControlNet (Zhang & Agrawala, 2023) proposed the usage of zero

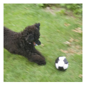
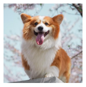
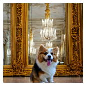
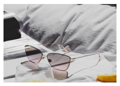
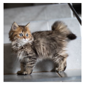
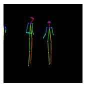
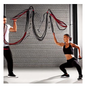
c_1	c_2	c_2	Task	y
A cartoon styled alarm clock	∅	∅	Text-to-Image Generation	
		Change frisbee to a football	Mask-guided Image Editing	
	Make it a slice of pizza instead of the sandwich	∅	Text-guided Image Editing	
	A [V] dog in the Versailles hall of mirrors	∅	Subject-Driven Image Generation	
		Replace glasses with [V] glasses	Subject-Driven Image Editing	
		A cat [V] standing by a pot [M]	Multi-Concept Image Composition	
	A small dog is curled up on top of the shoes	∅	Control-guided Image Generation	

Figure 3: The visualization of all the conditional image generation tasks. Here we consider tasks with 1-3 conditions, where ∅ means empty. The special token [V] and [M] are special identifiers.

convolution on the Stable Diffusion model to support additional guided image control. This work brings up the idea of the control-guided image generation task and inspired later work (Qin et al., 2023) on improving the control versatility.

AI-generated Image Assessment. Evaluating AI-generated images holistically is a complex and open problem (Salimans et al., 2016). Researchers have proposed various automatic metrics. In the image quality aspect, Inception score (Salimans et al., 2016), FID (Heusel et al., 2017) are often used. These methods rely on statistics from an InceptionNet pre-trained on the ImageNet dataset. Despite being widely adopted due to their sensitivity to small changes in images, these metrics are not ideal. They are biased towards the ImageNet dataset, resulting in inadequate evaluations (Borji, 2021). Later works like LPIPS (Zhang et al., 2018) and DreamSim (Fu et al., 2023) proposed better ways to measure the perceptual similarity. In the semantic consistency aspect, the CLIP score (Hessel et al., 2021) is often used to measure the vision-language alignment between the generated image and the prompt. Researchers also worked on alternative methods such as BLIP score (Li et al., 2022) and ImageReward (Xu et al., 2023). However, in some tasks like subject-driven image generation and editing, the automatic measurement of semantic consistency is still an open problem. One long-established yet effective approach to assessing AI-generated image performance is to rely on human annotators to assess the visual quality (Denton et al., 2015; Isola et al., 2017; Meng et al., 2021; Chen et al., 2023). The downside is that it entails a reliance on human judgment, which can introduce subjectivity and potentially limit scalability. To mitigate the downsides, the human evaluation design has to be unambiguous and easy to follow.

4 Method

4.1 Human Evaluation Metrics

Our proposed metric can be used in all seven tasks with the same standard. We adopt two major evaluation metrics, namely semantic consistency SC and perceptive quality PQ. These two metrics measure the quality of the generated images from two aspects. The semantic consistency measures how well the generated image is aligned with the condition $X = [c_1, c_2, \cdots]$. Specifically, we define

Condition 1	Condition 2	Condition 3	SC rating
Inconsistent	Any	Any	0
Any	Inconsistent	Any	0
Any	Any	Inconsistent	0
Partially Consistent	Any	Any	0.5
Any	Partially Consistent	Any	0.5
Any	Any	Partially Consistent	0.5
Mostly Consistent	Mostly Consistent	Mostly Consistent	1.0

Subjects in image	Artifacts	Unusual sense	PQ rating
Unrecognizable	Any	Any	0
Any	Serious	Any	0
Recognizable	Moderate	Any	0.5
Recognizable	Any	Moderate	0.5
Recognizable	Little/None	Little/None	1.0

Table 1: Rating guideline for computing the SC and PQ score. Detail in subsection A.2.

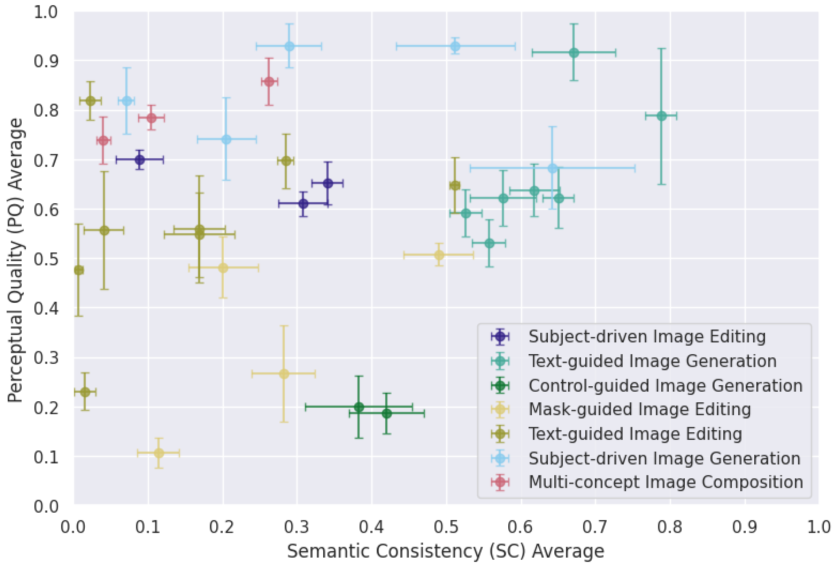


Figure 4: Model performance and standard deviation in each task.

the semantic consistency score as:

$$SC(y, X) = min\{g(y, c_1), g(y, c_2), \cdots, g(y, c_k)\} \tag{1}$$

where g is a modularized function to compute the consistency between y and a single condition c. We set $g(y, c_1) \in [0, 0.5, 1]$, where 0 means inconsistent, 0.5 means partially consistent and 1 means fully consistent. With this formulation, as long as the output is inconsistent with any of the conditions, the evaluation score should become zero. Otherwise, the aggregation function will pick the lowest consistency score from all the conditions. On the other hand, perceptive quality measures the image quality, i.e. whether the image contains artifacts, is blurry, or has an unnatural sense. we set perceptive quality $PQ \in [0, 0.5, 1]$, where 0 means extremely poor quality, 0.5 means the image has an acceptable quality and 1 means high quality. In these experiments, each model is rated individually. We train human raters to estimate the g function and PQ function with comprehensive guidelines in Table 1. We derive $O = \sqrt{SC \times PQ}$ as the overall rating of a model. One benefit of using geometric mean as the design choice is that the rating is penalized when one of the aspect scores is too low. We further studied the configuration in section 5.

Task	Data Source	Inference Dataset size
Text-guided Image Generation	DrawBench (Saharia et al., 2022) DiffusionDB (Wang et al., 2022) ABC-6K (Feng et al., 2023) Ours	197
Mask-guided Image Editing	MagicBrush (Zhang et al., 2023) Ours	179
Text-guided Image Editing	MagicBrush (Zhang et al., 2023) Ours	179
Subject-driven Image Generation	SuTI (Chen et al., 2023) Ours	150
Multi-concept Image Composition	CustomDiffusion (Kumari et al., 2023) Ours	102
Subject-driven Image Editing	DreamEditBench (Li et al., 2023b)	154
Control-guided Image Generation	HuggingFace community	150

Table 2: All the human evaluation datasets from seven core tasks.

4.2 Dataset and available models

We present a standardized dataset for each type of task. The information of the datasets is shown in Table 2. Some models have different standards of inputs in one task. For example, in the text-guided image editing task, DiffEdit is global description-guided while InstructPix2Pix is instruction-guided. We manually created the equivalent meaning prompts for both methods so they can be aligned. All datasets contain a huge variety of test cases to mimic the diversity in real-life situations. We hosted all of our datasets on the HuggingFace dataset for easy access and maintenance. Here we demonstrate all the evaluated models in Table 3.

5 Experimental Results

Experiment Setup. All the models either used the default setting from the official implementation or the setting suggested in HuggingFace documentation (von Platen et al., 2022). We disabled negative prompts and any prompt engineering tricks to ensure a fair comparison. We conducted human evaluation by recruiting participants from Prolific to rate the images, and our own researchers also took part in the image rating process. We assigned 3 raters for each model and computed the SC score, PQ score, and Overall human score. Then we computed the Fleiss kappa (Fleiss & Cohen, 1973) for each mentioned score. We also computed Krippendorff's Alpha (Krippendorff, 2011), which is expected to yield a higher value than Fleiss kappa. This distinction arises from the nature of the rating categories, with Fleiss' Kappa assuming nominal categories and Krippendorff's Alpha accommodating ordinal inputs. Both Fleiss' Kappa and Krippendorff's Alpha are bounded within the range of [-1, 1], where the value > 0 indicates an agreement and closer proximity to 1 indicates a higher degree of agreement. The design choices are explained in subsection 5.2 and Appendix A.6.

Results. In Figure 4, we present an overview of the model performance across various tasks. Our findings indicate that the performance of the current models is generally underwhelming, with the exception being Text-guided Image Generation and Subject-driven Image Generation, which have models reaching higher than 0.6 on both SC and PQ averages. The detailed report on each model's performance is shown on Table 4. We noticed that the overall automated metrics' correlation with the SC score and PQ score in each task is below 0.2 except subject-driven image editing task. Metric values are at Table 5 and Table 6.

5.1 Discovery and Insights

Text-Guided Image Generation. We observe that all models are able to generate high-quality images. Regarding semantic consistency, all models have a good understanding of the general prompts, while Stable Diffusion XL is better at understanding complex prompts. For example, it exhibits a high degree of accuracy and detail on the prompt "A panda making latte art." while other models

Model	#Params	Runtime	Keywords for technical detail
Text-to-Image Generation			
Dalle-3 (openai, 2023)	-	-	Recaptioned training data
MidJourney (midjourney, 2023)	-	-	-
Dalle-2 (Ramesh et al., 2022)	3.5B	10s	unCLIP, two-stage
Stable Diffusion (Rombach et al., 2022)	0.8B	3s	Latent Diffusion
DeepFloydIF (deep floyd.ai, 2023)	4.3B	37s	Cascaded Pixel Diffusion
OpenJourney (openjourney.ai, 2023)	0.8B	3s	SD, Midjourney data
Stable Diffusion XL (stability.ai, 2023)	2.3B	11s	Stable Diffusion, X-Large
Mask-guided Image Editing			
BlendedDiffusion (Avrahami et al., 2022)	0.5B	57s	Noise Blending, DDPM+CLIP
GLIDE (Nichol et al., 2022)	3.5B	19s	CLIP, Diffusion
SD-Inpaint (runwayml, 2023)	1.1B	11s	SD, Inpainting training
SDXL-Inpaint (stability.ai, 2023)	2.7B	36s	SDXL, Inpainting training
Text-guided Image Editing			
SDEdit (Meng et al., 2021)	1.3B	13s	SDE Prior
Text2Live (Bar-Tal et al., 2022)	3.1M	36s	Zero-shot, Edit layer
DiffEdit (Couairon et al., 2022)	1.3B	29s	Mask estimation
Cycle Diffusion (Wu & la Torre, 2023)	1.1B	9s	DPM-Encoder, Zero-shot
Prompt-to-Prompt (Mokady et al., 2022)	1.1B	2m	Cross-Attention
Pix2PixZero (Parmar et al., 2023)	1.1B	21s	Cross-Attention, Zero Prompt
InstructPix2Pix (Brooks et al., 2023)	1.1B	11s	SD, synthetic P2P data
MagicBrush (Zhang et al., 2023)	1.1B	7s	SD, MagicBrush data
Subject-driven Image Generation			
Textual Inversion (Gal et al., 2022)	1.1B	15m	Word embedding tuning
DreamBooth (Ruiz et al., 2023)	1.1B	10m	Finetuning with preservation loss
DreamBooth-Lora (Hu et al., 2021)	1.1B	8m	DreamBooth + Low-Rank Adaptation
SuTI (Chen et al., 2023)	2.5B	30s	In-context + Apprenticeship learning
BLIP-Diffusion (Li et al., 2023a)	1.1B	8s	Pretrained encoder, Zero-shot
Subject-driven Image Editing			
DreamEdit (Li et al., 2023b)	1.1B	8m	Dreambooth + Region proposal
PhotoSwap (Gu et al., 2023)	1.1B	7m	Dreambooth + Cross-Attention
BLIP-Diffusion (Li et al., 2023a)	1.1B	18s	Pretrained encoder, Zero-shot
Multi-concept Image Composition			
CustomDiffusion (Kumari et al., 2023)	1.1B	19m	Cross-attention updating
DreamBooth (Ruiz et al., 2023)	1.1B	11m	Finetuning with preservation loss
TextualInversion (Gal et al., 2022)	1.1B	32m	Word embedding tuning
Control-guided Image Generation			
ControlNet (Zhang & Agrawala, 2023)	1.4B	8s	Zero convolution + Frozen model
UniControl (Qin et al., 2023)	1.4B	23s	Multi-task pretraining, Zero-shot

Table 3: Overview of all the evaluated models and their parameter size and runtime. The models are listed in chronological order. The number of parameters and runtime for Dalle-3 and MidJourney are unknown. MidJourney is not opensource and does not have a whitepaper in technical detail.

often misunderstood the prompt as “panda latte art”. DALLE-3 and Midjourney understand most of the complex prompts than other models, and DALLE-3 is slightly better on conflicting prompts.

Mask-guided Image Editing. We observed the outputs commonly contain obvious artifacts in the masked region boundaries for Stable Diffusion and GLIDE. While Blended Diffusion and Stable Diffusion XL do not suffer from the same issue, they often produce unrecognizable outputs. Stable Diffusion XL obtains the best results but the overall model performance is still far from satisfactory. Another common issue is that the filled regions can hardly harmonize with the background.

Text-guided Image Editing. One key requirement is to edit the image precisely and keep the background untouched. This requirement is indeed challenging because the network has to understand of editing region from the semantic inputs. We discovered that Prompt-to-Prompt, Pix2PixZero, and SDEdit, despite generating high-quality images, often result in completely different backgrounds. We also spotted that in many cases Text2Live will simply return the input as output, this phenomenon

Model	LPIPS ↓	CLIP ↑	SC_{Avg}	PQ_{Avg}	Overall	Fleiss$_{\bar{O}}$	Kd$_{\bar{O}}$
Text-guided Image Generation							
Dalle-3	N/A	0.2697	0.79±0.02	0.79±0.14	**0.76±0.08**	0.19	0.34
Midjourney	N/A	0.2839	0.67±0.06	0.92±0.06	0.73±0.07	0.34	0.51
DeepFloydIF	N/A	0.2814	0.65±0.02	0.62±0.06	0.59±0.02	0.32	0.51
Stable Diffusion XL	N/A	0.2886	0.62±0.03	0.64±0.05	0.59±0.03	0.37	0.61
Dalle-2	N/A	0.2712	0.58±0.04	0.62±0.06	0.54±0.04	0.27	0.40
OpenJourney	N/A	0.2814	0.53±0.02	0.59±0.05	0.50±0.02	0.30	0.47
Stable Diffusion 2.1	N/A	0.2899	0.56±0.02	0.53±0.05	0.50±0.03	0.38	0.50
Mask-guided Image Editing							
SDXL-Inpainting	0.15	0.2729	0.49±0.05	0.51±0.02	**0.37±0.05**	0.50	0.72
SD-Inpainting	0.21	0.2676	0.28±0.04	0.27±0.10	0.17±0.07	0.31	0.49
GLIDE	0.18	0.2578	0.20±0.05	0.48±0.06	0.16±0.05	0.33	0.56
BlendedDiffusion	0.33	0.2594	0.12±0.03	0.11±0.03	0.05±0.02	0.36	0.44
Text-guided Image Editing							
MagicBrush	0.22	0.2675	0.51±0.01	0.65±0.06	**0.47±0.02**	0.44	0.67
InstructPix2Pix	0.32	0.2616	0.29±0.01	0.70±0.06	0.27±0.02	0.55	0.74
Prompt-to-prompt	0.40	0.2674	0.17±0.05	0.55±0.09	0.15±0.06	0.36	0.53
CycleDiffusion	0.28	0.2692	0.17±0.03	0.56±0.11	0.14±0.04	0.41	0.63
SDEdit	0.61	0.2872	0.04±0.03	0.56±0.12	0.04±0.03	0.13	0.13
Text2Live	0.17	0.2628	0.02±0.01	0.82±0.04	0.02±0.02	0.10	0.17
DiffEdit	0.22	0.2425	0.02±0.01	0.23±0.04	0.01±0.01	0.24	0.24
Pix2PixZero	0.60	0.2510	0.01±0.00	0.48±0.09	0.01±0.01	0.37	0.37
Subject-driven Image Generation							
SuTI	0.77	0.2895	0.64±0.11	0.68±0.08	**0.58±0.12**	0.20	0.39
DreamBooth	0.77	0.2847	0.51±0.08	0.93±0.02	0.55±0.11	0.37	0.60
BLIP-Diffusion	0.77	0.2729	0.29±0.04	0.93±0.04	0.35±0.06	0.22	0.39
TextualInversion	0.81	0.2680	0.21±0.04	0.74±0.08	0.21±0.05	0.35	0.52
DreamBooth-Lora	0.82	0.2988	0.07±0.01	0.82±0.07	0.09±0.01	0.29	0.37
Subject-driven Image Editing							
PhotoSwap	0.34	0.2846	0.34±0.02	0.65±0.04	**0.36±0.02**	0.35	0.46
DreamEdit	0.22	0.2855	0.31±0.03	0.61±0.03	0.32±0.03	0.33	0.52
BLIP-Diffusion	0.25	0.2901	0.09±0.03	0.70±0.02	0.09±0.03	0.41	0.47
Multi-concept Image Composition							
CustomDiffusion	0.79	0.2929	0.26±0.01	0.86±0.05	**0.29±0.01**	0.73	0.88
DreamBooth	0.78	0.2993	0.11±0.02	0.78±0.02	0.13±0.02	0.61	0.71
TextualInversion	0.80	0.2548	0.04±0.01	0.74±0.05	0.05±0.01	0.62	0.77
Control-guided Image Generation							
ControlNet	0.80	0.2555	0.42±0.05	0.19±0.04	**0.23±0.04**	0.37	0.57
UniControl	0.82	0.2604	0.38±0.07	0.20±0.06	0.23±0.07	0.36	0.58

Table 4: All the evaluated models from seven core tasks. Overall is the average of all $\sqrt{SC \times PQ}$. Fleiss$_{\bar{O}}$ and Kd$_{\bar{O}}$, denoting Fleiss' Kappa and Krippendorff's alpha for the overall average, respectively. We have more automated metric results in Appendix Table 5 and correlations in Table 6.

also occasionally happened in other models. For paper claims, our evaluation ranking aligns with the findings from CycleDiffsuion, InstructPix2Pix, MagicBrush, Prompt-to-Prompt, and DiffEdit. We found our evaluation ranking does not align with Pix2PixZero, since their paper only tested on word-swapping examples, which is not able to generalize to more complex edits.

Subject-driven Image Generation. Our evaluation results largely align with DreamBooth, BLIP-Diffusion, and SuTI findings. Specifically, Textual inversion struggles to maintain target subject features. DreamBooth can imitate subjects based on images but occasionally resorts to copying learned images. DreamBooth-Lora struggles to generate desired subjects but can follow context prompts. BLIP-Diffusion can mimic target subject features but struggles with details. SuTI maintains high consistency with desired subjects and context, with tolerable artifacts in some cases.

Multi-concept Image Composition. Our evaluations validate that CustomDiffusion is consistently better than the other two models. However, while it learns the given multiple subjects' features better, it could fail to follow the prompts in many cases, especially on actions and positional words. In contrast, DreamBooth learns the correct subjects in some cases, and TextualInversion rarely learns the correct subjects. Interestingly, in some cases where DreamBooth does not learn the correct subjects, it could still follow the prompts correctly.

Subject-driven Image Editing. It is essential to modify the subject from the source to the target without causing excess changes to the background. Human evaluation is also conducted in DreamEdit for the comparison between Photoswap and DreamEdit, but our rankings differ due to varying evaluation criteria. PhotoSwap can adapt to the target subject from the source naturally in most cases but rarely preserves the background well. DreamEdit maintains the context in most cases but sometimes leaves observable distortions at the edge of contextualization. BLIP-Diffusion fails the adaptation most of the time, compromising for a more realistic generation.

Control-guided Image Generation. Our evaluation shows there is no significant difference between the two models in both automatic metrics and human evaluation metrics. While UniControl also reported that there is no significant difference in automatic metrics, our human evaluation results do not align. This can be due to the different evaluation standards and aspects. Nevertheless, it has come to our attention that neither of these models demonstrates a high level of robustness. Scratches often appeared on the generated image.

5.2 Ablation Study

Method of overall human score computation. We set the overall score of the model as the geometric mean of SC and PR score (i.e. $O = \sqrt{SC \times PQ}$). But we also explored the weighted sum setting $O = \alpha \times SC + \beta \times PQ$, where both α and β are in [0, 1]. We experimented and found that the weighted sum setting yields a different ranking in the models. Take the text-guided image editing task as an example, as in Appendix Table 7, Text2Live outperforms CycleDiffusion in the weighted sum setting even though we found that CycleDiffusion performs better in the human examination. We investigated and found that a majority of results in Text2Live simply return the input as output (in that case SC=0 and PQ=1). We tried adjusting the weightings but it still failed to reflect the actual performance of the model. Thus we decided to use the geometric mean setting to penalize the models.

Design choice of human evaluation metric range. When it comes to human evaluation on a massive scale, it's essential to create a system that's easy to understand and quick to use. In this investigation, we undertake an exploration into how different settings in this evaluation method can affect the results, showing in Appendix Table 8. Initially, our approach entailed the utilization of a range encompassing [0, 0.5, 1, 2] for both the Semantic Consistency (SC) score and the Perception Quality (PQ) score, where 2 means the image is perfect. However, this configuration yielded suboptimal results in the Fleiss Kappa. Subsequently, an alternative configuration was employed, narrowing the range to [0, 1] for both the SC and PQ scores. This adjustment, while accommodating a binary classification, was observed to yield values that were overly polarized and extreme. To find the right balance between keeping values in a reasonable range and making sure the evaluation method is reliable, we resolved to define a range of [0, 0.5, 1] while providing explicit and unambiguous guidelines.

Conclusion

In this paper, we propose ImagenHub as a continuous effort to unify all efforts in conditional image generation into a library, easing access to these models. We standardize the dataset and evaluation of these models to build our ImagenHub Leaderboard. We hope this leaderboard can provide a more reproducible and fair environment for researchers to visualize progress in this field. A limitation of this work is the reliance on human raters, which is expensive and time-consuming. In the future, we plan to develop more generic automatic evaluation methods that approximate human ratings, helping people develop better models.

Ethics Statement

Our work aims to benefit the broader research community by providing a standardized framework for evaluating conditional image generation models. For all the benchmarks, we are committed to the ethical use of them. The datasets used in our work are either publicly available or have been collected and curated exercising the utmost respect for privacy and consent. We will maintain a leaderboard to track latest models and encourage open collaboration and discussion in the field. In human evaluation, we followed the minimum hourly wage of $11. We also ensure that no personal information is collected and no offensive content is presented during human evaluations.

References

Omri Avrahami, Dani Lischinski, and Ohad Fried. Blended diffusion for text-driven editing of natural images. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 18208–18218, 2022.

Omer Bar-Tal, Dolev Ofri-Amar, Rafail Fridman, Yoni Kasten, and Tali Dekel. Text2live: Text-driven layered image and video editing. In *European Conference on Computer Vision*, pp. 707–723, 2022.

Ali Borji. Pros and cons of gan evaluation measures: New developments, 2021.

Tim Brooks, Aleksander Holynski, and Alexei A. Efros. Instructpix2pix: Learning to follow image editing instructions. In *CVPR*, 2023.

Wenhu Chen, Hexiang Hu, Yandong Li, Nataniel Rui, Xuhui Jia, Ming-Wei Chang, and William W Cohen. Subject-driven text-to-image generation via apprenticeship learning. *NeurIPS*, 2023.

Guillaume Couairon, Jakob Verbeek, Holger Schwenk, and Matthieu Cord. Diffedit: Diffusion-based semantic image editing with mask guidance. In *The Eleventh International Conference on Learning Representations*, 2022.

deep floyd.ai. If by deepfloyd lab at stabilityai, 2023. URL https://github.com/deep-floyd/IF.

Emily L Denton, Soumith Chintala, arthur szlam, and Rob Fergus. Deep generative image models using a laplacian pyramid of adversarial networks. In C. Cortes, N. Lawrence, D. Lee, M. Sugiyama, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 28. Curran Associates, Inc., 2015. URL https://proceedings.neurips.cc/paper_files/paper/2015/file/aa169b49b583a2b5af89203c2b78c67c-Paper.pdf.

Weixi Feng, Xuehai He, Tsu-Jui Fu, Varun Jampani, Arjun Reddy Akula, Pradyumna Narayana, Sugato Basu, Xin Eric Wang, and William Yang Wang. Training-free structured diffusion guidance for compositional text-to-image synthesis. In *The Eleventh International Conference on Learning Representations*, 2023. URL https://openreview.net/forum?id=PUIqjT4rzq7.

Joseph L Fleiss and Jacob Cohen. The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. *Educational and psychological measurement*, 33(3):613–619, 1973.

Stephanie Fu, Netanel Tamir, Shobhita Sundaram, Lucy Chai, Richard Zhang, Tali Dekel, and Phillip Isola. Dreamsim: Learning new dimensions of human visual similarity using synthetic data, 2023.

Rinon Gal, Yuval Alaluf, Yuval Atzmon, Or Patashnik, Amit H Bermano, Gal Chechik, and Daniel Cohen-Or. An image is worth one word: Personalizing text-to-image generation using textual inversion. *arXiv preprint arXiv:2208.01618*, 2022.

Jing Gu, Yilin Wang, Nanxuan Zhao, Tsu-Jui Fu, Wei Xiong, Qing Liu, Zhifei Zhang, He Zhang, Jianming Zhang, HyunJoon Jung, et al. Photoswap: Personalized subject swapping in images. *arXiv preprint arXiv:2305.18286*, 2023.

Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi. CLIPScore: a reference-free evaluation metric for image captioning. In *EMNLP*, 2021.

Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter. Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems*, 30, 2017.

Edward J Hu, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, Weizhu Chen, et al. Lora: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2021.

Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, and Alexei A Efros. Image-to-image translation with conditional adversarial networks. *CVPR*, 2017.

Klaus Krippendorff. Computing krippendorff's alpha-reliability, 2011. URL https://api.semanticscholar.org/CorpusID:59901023.

Nupur Kumari, Bingliang Zhang, Richard Zhang, Eli Shechtman, and Jun-Yan Zhu. Multi-concept customization of text-to-image diffusion. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1931–1941, 2023.

Dongxu Li, Junnan Li, and Steven CH Hoi. Blip-diffusion: Pre-trained subject representation for controllable text-to-image generation and editing. *arXiv preprint arXiv:2305.14720*, 2023a.

Junnan Li, Dongxu Li, Caiming Xiong, and Steven Hoi. Blip: Bootstrapping language-image pre-training for unified vision-language understanding and generation. In *ICML*, 2022.

Tianle Li, Max Ku, Cong Wei, and Wenhu Chen. Dreamedit: Subject-driven image editing. *arXiv preprint arXiv:2306.12624*, 2023b.

Chenlin Meng, Yutong He, Yang Song, Jiaming Song, Jiajun Wu, Jun-Yan Zhu, and Stefano Ermon. Sdedit: Guided image synthesis and editing with stochastic differential equations. In *International Conference on Learning Representations*, 2021.

midjourney. Midjourney, 2023. URL https://www.midjourney.com/home.

Ron Mokady, Amir Hertz, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Null-text inversion for editing real images using guided diffusion models. *arXiv preprint arXiv:2211.09794*, 2022.

Alexander Quinn Nichol, Prafulla Dhariwal, Aditya Ramesh, Pranav Shyam, Pamela Mishkin, Bob Mcgrew, Ilya Sutskever, and Mark Chen. Glide: Towards photorealistic image generation and editing with text-guided diffusion models. In *International Conference on Machine Learning*, pp. 16784–16804. PMLR, 2022.

openai. Improving image generation with better captions, 2023. URL https://cdn.openai.com/papers/dall-e-3.pdf.

openjourney.ai. Openjourney is an open source stable diffusion fine tuned model on midjourney images, 2023. URL https://huggingface.co/prompthero/openjourney.

Gaurav Parmar, Krishna Kumar Singh, Richard Zhang, Yijun Li, Jingwan Lu, and Jun-Yan Zhu. Zero-shot image-to-image translation. In *ACM SIGGRAPH 2023 Conference Proceedings*, pp. 1–11, 2023.

Or Patashnik, Zongze Wu, Eli Shechtman, Daniel Cohen-Or, and Dani Lischinski. Styleclip: Text-driven manipulation of stylegan imagery. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 2085–2094, October 2021.

Can Qin, Shu Zhang, Ning Yu, Yihao Feng, Xinyi Yang, Yingbo Zhou, Huan Wang, Juan Carlos Niebles, Caiming Xiong, Silvio Savarese, et al. Unicontrol: A unified diffusion model for controllable visual generation in the wild. *arXiv preprint arXiv:2305.11147*, 2023.

Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning*, 2021.

Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen. Hierarchical text-conditional image generation with clip latents. *arXiv preprint arXiv:2204.06125*, 1(2):3, 2022.

Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 10684–10695, 2022.

Nataniel Ruiz, Yuanzhen Li, Varun Jampani, Yael Pritch, Michael Rubinstein, and Kfir Aberman. Dreambooth: Fine tuning text-to-image diffusion models for subject-driven generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 22500–22510, 2023.

runwayml. Stable diffusion inpainting, 2023. URL https://huggingface.co/runwayml/stable-diffusion-inpainting.

Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton, Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al. Photorealistic text-to-image diffusion models with deep language understanding. *Advances in Neural Information Processing Systems*, 35:36479–36494, 2022.

Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, Xi Chen, and Xi Chen. Improved techniques for training gans. In D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett (eds.), *Advances in Neural Information Processing Systems*, volume 29. Curran Associates, Inc., 2016. URL https://proceedings.neurips.cc/paper_files/paper/2016/file/8a3363abe792db2d8761d6403605aeb7-Paper.pdf.

Kihyuk Sohn, Nataniel Ruiz, Kimin Lee, Daniel Castro Chin, Irina Blok, Huiwen Chang, Jarred Barber, Lu Jiang, Glenn Entis, Yuanzhen Li, et al. Styledrop: Text-to-image generation in any style. *arXiv preprint arXiv:2306.00983*, 2023.

stability.ai. Stable diffusion xl, 2023. URL https://stability.ai/stable-diffusion.

Patrick von Platen, Suraj Patil, Anton Lozhkov, Pedro Cuenca, Nathan Lambert, Kashif Rasul, Mishig Davaadorj, and Thomas Wolf. Diffusers: State-of-the-art diffusion models. https://github.com/huggingface/diffusers, 2022.

Zijie J. Wang, Evan Montoya, David Munechika, Haoyang Yang, Benjamin Hoover, and Duen Horng Chau. DiffusionDB: A large-scale prompt gallery dataset for text-to-image generative models. *arXiv:2210.14896 [cs]*, 2022. URL https://arxiv.org/abs/2210.14896.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, Rémi Louf, Morgan Funtowicz, et al. Huggingface's transformers: State-of-the-art natural language processing. *arXiv preprint arXiv:1910.03771*, 2019.

Chen Henry Wu and Fernando De la Torre. A latent space of stochastic diffusion models for zero-shot image editing and guidance. In *ICCV*, 2023.

Jiazheng Xu, Xiao Liu, Yuchen Wu, Yuxuan Tong, Qinkai Li, Ming Ding, Jie Tang, and Yuxiao Dong. Imagereward: Learning and evaluating human preferences for text-to-image generation, 2023.

Kai Zhang, Lingbo Mo, Wenhu Chen, Huan Sun, and Yu Su. Magicbrush: A manually annotated dataset for instruction-guided image editing. *NeurIPS dataset and benchmark track*, 2023.

Lvmin Zhang and Maneesh Agrawala. Adding conditional control to text-to-image diffusion models. *arXiv preprint arXiv:2302.05543*, 2023.

Richard Zhang, Phillip Isola, Alexei A Efros, Eli Shechtman, and Oliver Wang. The unreasonable effectiveness of deep features as a perceptual metric. In *CVPR*, 2018.

A APPENDIX

A.1 MORE METRICS RESULTS

Model	LPIPS ↓	DINO ↑	CLIP-I ↑	DreamSim ↓	FID ↓	KID ↓	CLIP ↑
Text-guided Image Generation							
Dalle-3	N/A	N/A	N/A	N/A	N/A	N/A	0.2697
MidJourney	N/A	N/A	N/A	N/A	N/A	N/A	0.2839
DeepFloydIF	N/A	N/A	N/A	N/A	N/A	N/A	0.2814
Stable Diffusion XL	N/A	N/A	N/A	N/A	N/A	N/A	0.2886
Dalle-2	N/A	N/A	N/A	N/A	N/A	N/A	0.2712
OpenJourney	N/A	N/A	N/A	N/A	N/A	N/A	0.2814
Stable Diffusion	N/A	N/A	N/A	N/A	N/A	N/A	0.2899
Mask-guided Image Editing							
SDXL-Inpainting	0.15	0.90	0.94	0.15	59.04	-0.0033	0.2729
SD-Inpainting	0.21	0.85	0.91	0.20	86.23	-0.0008	0.2676
GLIDE	0.18	0.91	0.94	0.14	61.71	-0.0028	0.2578
BlendedDiffusion	0.33	0.80	0.87	0.26	102.73	-0.0012	0.2594
Text-guided Image Editing							
MagicBrush	0.22	0.88	0.92	0.19	77.81	-0.0027	0.2675
InstructPix2Pix	0.32	0.77	0.86	0.30	100.30	-0.0014	0.2616
Prompt-to-prompt	0.40	0.68	0.81	0.36	137.68	0.0003	0.2674
CycleDiffusion	0.28	0.79	0.88	0.27	108.29	-0.0008	0.2692
SDEdit	0.61	0.57	0.76	0.50	156.12	0.0025	0.2872
Text2Live	0.17	0.87	0.92	0.18	68.33	-0.0028	0.2628
DiffEdit	0.22	0.78	0.85	0.31	121.79	0.0069	0.2425
Pix2PixZero	0.60	0.53	0.76	0.52	161.64	0.0072	0.2510
Subject-driven Image Generation							
SuTI	0.77	0.69	0.81	0.32	164.97	0.0111	0.2895
DreamBooth	0.77	0.61	0.80	0.40	173.71	0.0057	0.2847
BLIP-Diffusion	0.77	0.63	0.82	0.36	166.53	0.0102	0.2729
TextualInversion	0.81	0.37	0.65	0.61	229.18	0.0122	0.2680
DreamBooth-Lora	0.82	0.36	0.70	0.61	234.95	0.0125	0.2988
Subject-driven Image Editing							
PhotoSwap	0.34	0.65	0.83	0.37	130.81	0.0009	0.2846
DreamEdit	0.22	0.74	0.87	0.28	118.95	0.0011	0.2855
BLIP-Diffusion	0.25	0.80	0.89	0.23	102.17	0.0007	0.2901
Multi-concept Image Composition							
CustomDiffusion	0.79	0.50	0.70	0.55	207.43	0.0341	0.2929
DreamBooth	0.78	0.39	0.64	0.66	257.60	0.0533	0.2993
TextualInversion	0.80	0.44	0.66	0.65	226.25	0.0491	0.2548
Control-guided Image Generation							
ControlNet	0.80	0.43	0.70	0.56	219.29	0.0330	0.2555
UniControl	0.82	0.42	0.68	0.58	222.57	0.0192	0.2604

Table 5: All automated metrics for the evaluated models based on our benchmark dataset.

	PQ ↑				SC ↑
Task	corr(LPIPS)	corr(DINO)	corr(CLIP-I)	corr(DreamSim)	corr(CLIP)
Text-guided Image Generation	N/A	N/A	N/A	N/A	-0.0819
Mask-guided Image Editing	-0.0502	-0.0421	-0.0308	-0.0294	-0.0257
Text-guided Image Editing	0.0439	0.0449	0.0765	0.0432	0.0437
Subject-driven Image Generation	0.0905	0.1737	0.1204	0.0943	-0.0117
Subject-driven Image Editing	0.2417	0.1690	0.3770	0.3846	-0.0443
Multi-concept Image Composition	-0.1018	-0.1657	-0.0965	0.0140	-0.0107
Control-guided Image Generation	0.1864	0.1971	-0.0985	-0.0045	-0.2056

Table 6: Metrics correlation. we inverted the signs for metric that is the lower the better. The computable metrics all hold different assumptions which only contribute part of the aspects in human evaluation. This makes a low correlation with human evaluations.

Setting	$O = \sqrt{SC \times PQ}$		$O = 0.5SC + 0.5PQ$		$O = 0.7SC + 0.3PQ$	
	O_{Sum}	O_{Avg}	O_{Sum}	O_{Avg}	O_{Sum}	O_{Avg}
MagicBrush	83.51	0.47	103.75	0.58	98.85	0.55
CycleDiffusion	24.89	0.14	65.25	0.36	51.28	0.29
DiffEdit	1.71	0.01	22.08	0.12	14.38	0.08
Text2Live	4.08	0.02	75.25	0.42	46.75	0.26

Table 7: Comparison on overall human score computation setting.

Setting	categories = [0, 0.5, 1]			categories = [0, 0.5, 1, 2]			categories = [0, 1]		
	O_{Avg}	Fleiss$_{\bar{O}}$	Kd$_{\bar{O}}$	O_{Avg}	Fleiss$_{\bar{O}}$	Kd$_{\bar{O}}$	O_{Avg}	Fleiss$_{\bar{O}}$	Kd$_{\bar{O}}$
BLIP-Diffusion	0.13	0.41	0.47	0.09	0.29	0.50	0.05	0.40	0.40
DreamEdit	0.50	0.33	0.52	0.32	0.26	0.55	0.21	0.38	0.38
PhotoSwap	0.62	0.35	0.46	0.36	0.25	0.50	0.29	0.37	0.37

Table 8: Ablation study to understand the impact of the granularity of SC and PQ.

A.2 Human Evaluation Guideline

To standardize the conduction of a rigorous human evaluation, we stipulate the criteria for each measurement as follows:

- Semantic Consistency (SC), score in range [0, 0.5, 1]. It measures the level that the generated image is coherent in terms of the condition provided (i.e. Prompts, Subject Token, etc.).
- Perceptual Quality (PQ), score in range [0, 0.5, 1]. It measures the level at which the generated image is visually convincing and gives off a natural sense.

Meaning of Semantic Consistency (SC) score:

- SC=0 : Image not following one or more of the conditions at all (e.g. not following the prompt at all, different background in editing task, wrong subject in subject-driven task, etc.)
- SC=0.5 : all the conditions are partly following the requirements.
- SC=1 : The rater agrees that the overall idea is correct.

Meaning of Perceptual Quality (PQ) score:

- PQ=0 : The rater spotted obvious distortion or artifacts at first glance and those distorts make the objects unrecognizable.
- PQ=0.5 : The rater found out the image gives off an unnatural sense. Or the rater spotted spotted some minor artifacts and the objects are still recognizable.
- PQ=1 : The rater agrees that the resulting image looks genuine.

Raters have to strictly adhere to Table 9 when rating.

Condition 1	Condition 2 (if applicable)	Condition 3 (if applicable)	SC rating
no following at all	Any	Any	0
Any	no following at all	Any	0
Any	Any	no following at all	0
following some part	following some or most part	following some or most part	0.5
following some or most part	following some part	following some or most part	0.5
following some part or more	following some or most part	following some part	0.5
following most part	following most part	following most part	1

Objects in image	Artifacts	Unusual sense	PQ rating
Unrecognizable	serious	Any	0
Recognizable	some	Any	0.5
Recognizable	Any	some	0.5
Recognizable	none	little or None	1

Table 9: Rating guide checklist table.

Artifacts and Unusual sense, respectively, are:

- Distortion, watermark, scratches, blurred faces, unusual body parts, subjects not harmonized
- wrong sense of distance (subject too big or too small compared to others), wrong shadow, wrong lighting, etc.

A.3 Rating Examples

There are some examples when evaluating:

Text-to-Image Generation.

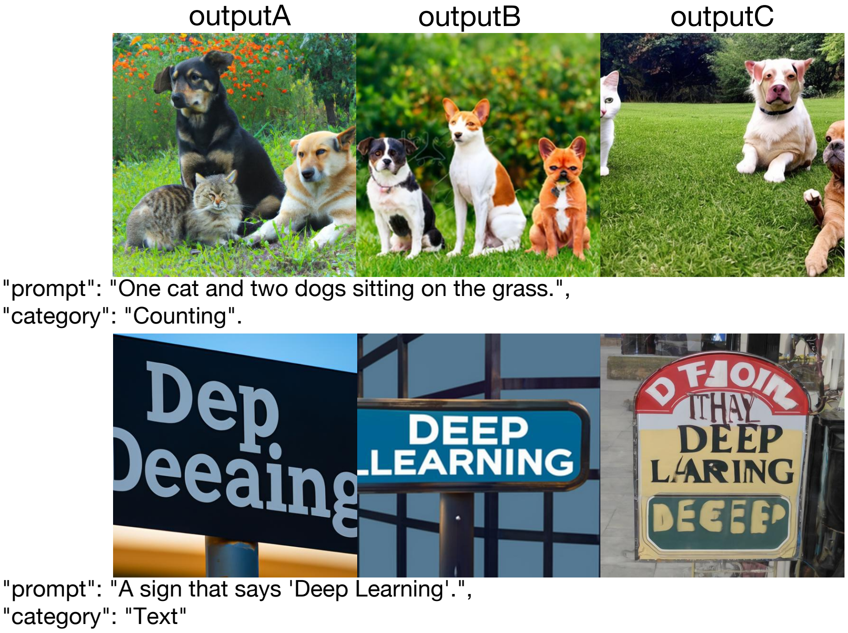
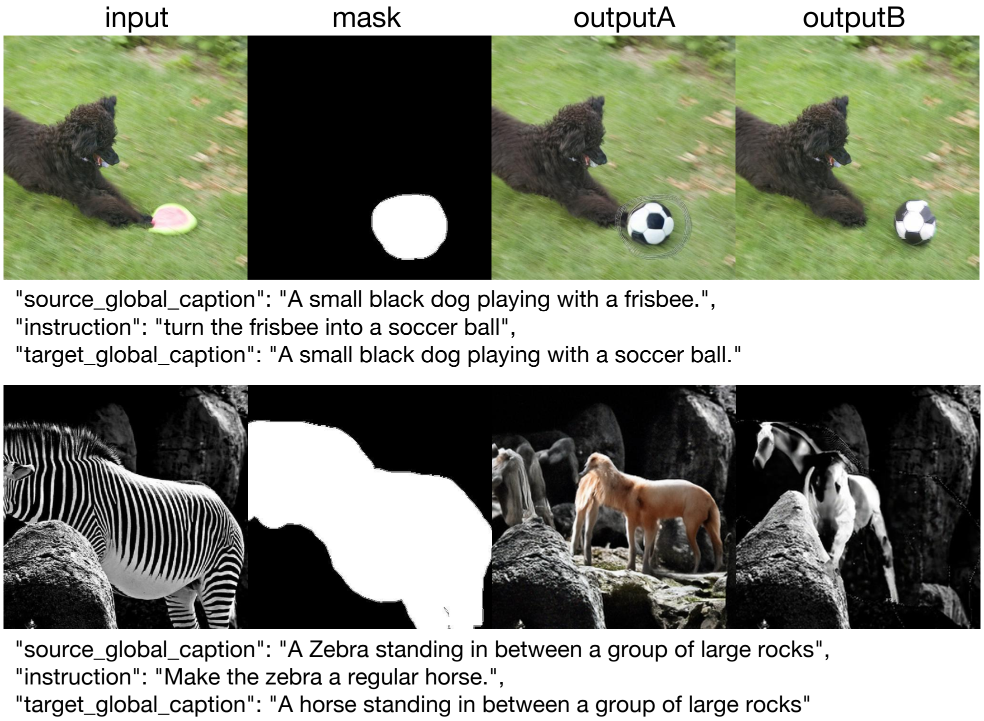

outputA
outputB
outputC
"prompt": "One cat and two dogs sitting on the grass.",
"category": "Counting".
Dep
Deeaing
DEEP
LEARNING
DEEP
LARING
DECEEP
"prompt": "A sign that says 'Deep Learning'.",
"category": "Text"

Figure 5: Rating examples on Text-to-Image Generation task.

- OutputA$_1$: `[1, 0.5]`. SC=1: Prompt perfectly align. PR=0.5: Minor distortion on the cat's facial features.
- OutputB$_1$: `[0.5, 0.5]`. SC=0.5: 3 dogs appeared instead of 1 cat and 2 dogs. PR=0.5: Minor distortion was found on the animal's face and the watermark.
- OutputC$_1$: `[1, 0.5]`. SC=1: The prompt match perfectly with the image. PR=0.5: Minor distortion on the dog's facial features.
- OutputA$_2$: `[0.5, 1]`. SC=0.5: A sign appeared, but failed to spell the word. PR=1: The image look generally real but with some lighting issues.
- OutputB$_2$: `[0.5, 0.5]`. SC=0.5: A sign appeared, but failed to spell the word. PR=0.5: The background looks so unnatural.
- OutputC$_2$: `[0.5, 0]`. SC=0.5: A sign appeared, but failed to spell the word. PR=0: Heavy distortion on both text and strong artifacts in the background.

Mask-guided Image Editing.



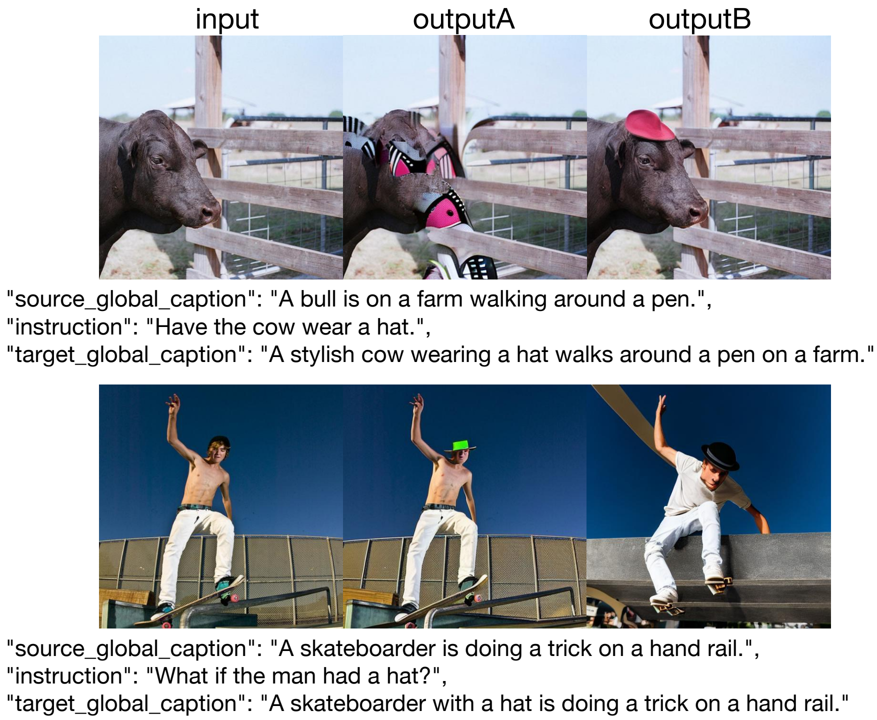
"source_global_caption": "A small black dog playing with a frisbee.",
"instruction": "turn the frisbee into a soccer ball",
"target_global_caption": "A small black dog playing with a soccer ball."

"source_global_caption": "A Zebra standing in between a group of large rocks",
"instruction": "Make the zebra a regular horse.",
"target_global_caption": "A horse standing in between a group of large rocks"

Figure 6: Rating examples on Mask-guided Image Editing task.

- OutputA$_1$: `[1, 0.5]`. SC=1: Clearly generate the soccer. PR=0.5: The edit region does not blend well with the context.
- OutputB$_1$: `[1, 1]`. SC=1: Successfully add a soccer. PR=1: The soccer is naturally blended with the context.
- OutputA$_2$: `[0, 0]`. SC=0: Generated content can not be regarded as horse. PR=0: The middle left part is not natural.
- OutputB$_2$: `[0.5, 0]`. SC=0.5: The object is horse-like but not good. PR=0: The whole image is not natural.

Text-guided Image Editing.



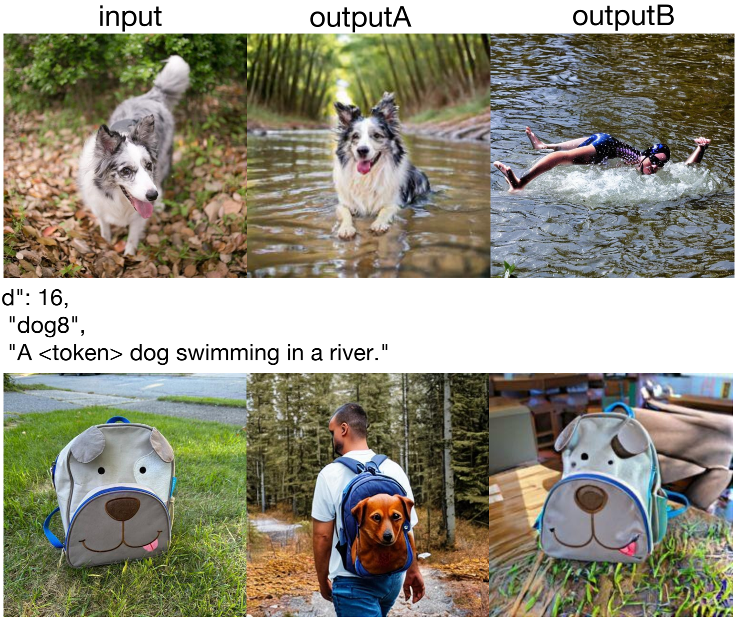
"source_global_caption": "A bull is on a farm walking around a pen.",
"instruction": "Have the cow wear a hat.",
"target_global_caption": "A stylish cow wearing a hat walks around a pen on a farm."

"source_global_caption": "A skateboarder is doing a trick on a hand rail.",
"instruction": "What if the man had a hat?",
"target_global_caption": "A skateboarder with a hat is doing a trick on a hand rail."

Figure 7: Rating examples on Text-guided Image Editing task.

- OutputA$_1$: `[0, 0]`. SC=0: The image does not follow the instruction at all. PR=0: Heavy distortion on the cow's facial features.
- OutputB$_1$: `[1, 1]`. SC=1: The hat gives a nice specular reflection. PR=1: It looks real.
- OutputA$_2$: `[0.5, 0.5]`. SC=0.5: The hat exists but does not suit well. PR=0.5: The important object look distorted.
- OutputB$_2$: `[0, 0]`. SC=0: The background completely changed. PR=0: The whole image look distorted.

Subject-driven Image Generation.



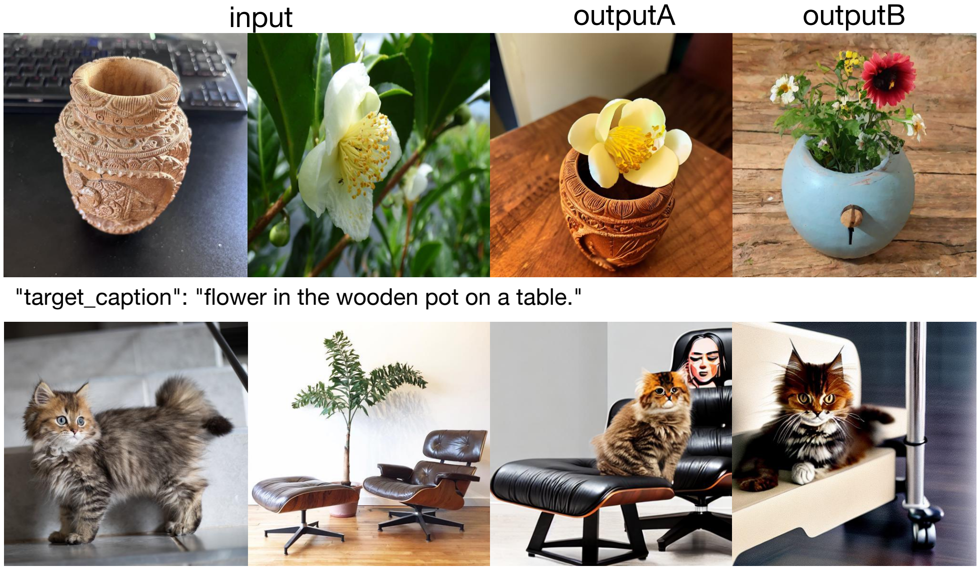
"subject_id": 16,
"subject": "dog8",
"prompt": "A <token> dog swimming in a river."

"subject_id": 1,
"subject": "backpack_dog",
"prompt": "a man carrying <token> backpack dog."

Figure 8: Rating examples on Subject-driven Image Generation task.

- OutputA$_1$: `[1, 1]`. SC=1: The output does match the subject and prompt. PR=1: It looks real.
- OutputB$_1$: `[0, 0]`. SC=0: The subject dog missing. PR=0: Serious unusual body.
- OutputA$_2$: `[0, 0.5]`. SC=0: The output does not match the subject. PR=0.5: Some unusual sense on the backpack.
- OutputB$_2$: `[0, 0.5]`. SC=0: The output does not match the prompt. PR=0.5: Some unusual sense on the desk with the grass.

Multi-concept Image Composition.



"target_caption": "flower in the wooden pot on a table."

"target_caption": "chair with a screaming cat sitting on it."

Figure 9: Rating examples on Multi-concept Image Composition task.

- OutputA$_1$: [1, 1]. SC=1: Both subjects accurately represent the intended subjects and the prompt actions match. PR=1: In general the image is natural and as real.
- OutputB$_1$: [0, 1]. SC=0: Subjects are not correct even though prompt action matches. PR=1: The image looks real.
- OutputA$_2$: [0.5, 0.5]. SC=0.5: Both subjects accurately represent the intended subjects and but the prompt action doesn't match. PR=0.5: There is a human face on the chair so the important subject chair looks unrealistic, but do not strongly detract from the image's overall appearance.
- OutputB$_2$: [0, 0.5]. SC=0: Subject chair missing. PR=0.5: Minor distortion on the cat body and background.

Subject-driven Image Editing.

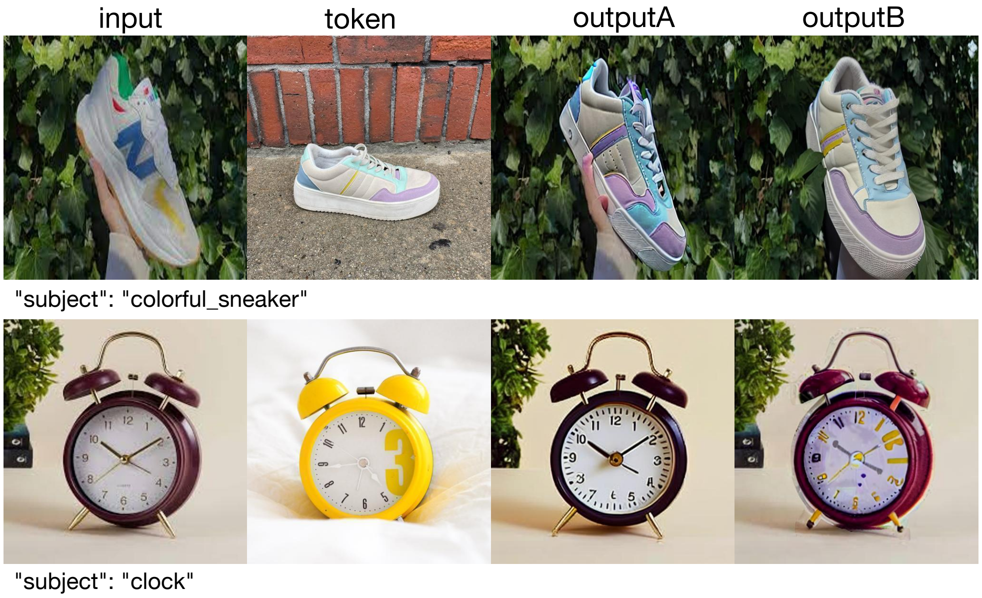
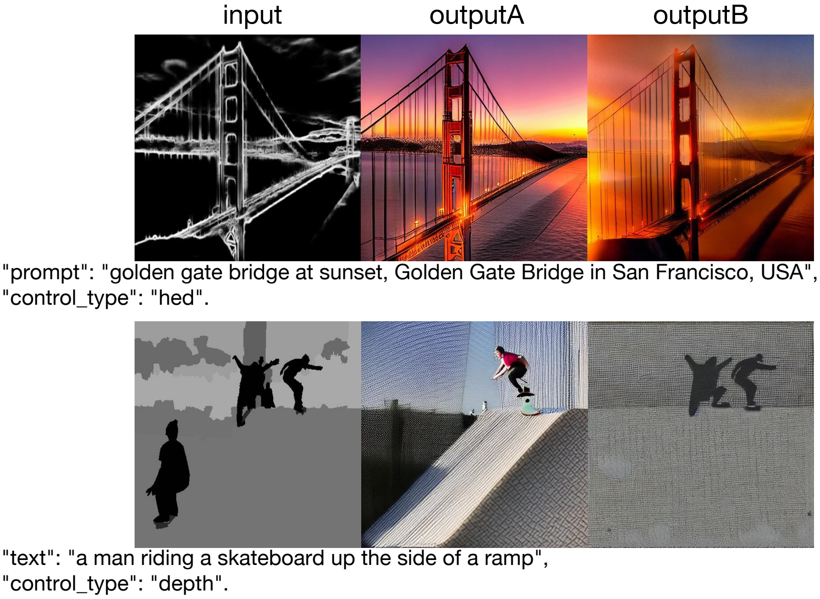


Figure 10: Rating examples on Subject-driven Image Editing task.

- OutputA$_1$: `[0.5, 0.5]`. SC=0.5: Some details of the subject do not match the token. PR=0.5: Some unnatural sense on the hand features.
- OutputB$_1$: `[0.5, 1]`. SC=0.5: The subject does match the token, but removing the hand is an unnecessary edit. PR=1: It looks real.
- OutputA$_2$: `[0, 0.5]`. SC=0: Subject clock does not match. PR=0.5: Some distortion on the numbers of the clock.
- OutputB$_2$: `[0, 0.5]`. SC=0: Subject clock does not match. PR=0.5: Some distortion on the numbers of the clock and the edit region does not blend well with the context.

Control-guided Image Generation.



"prompt": "golden gate bridge at sunset, Golden Gate Bridge in San Francisco, USA",
"control_type": "hed".

"text": "a man riding a skateboard up the side of a ramp",
"control_type": "depth".

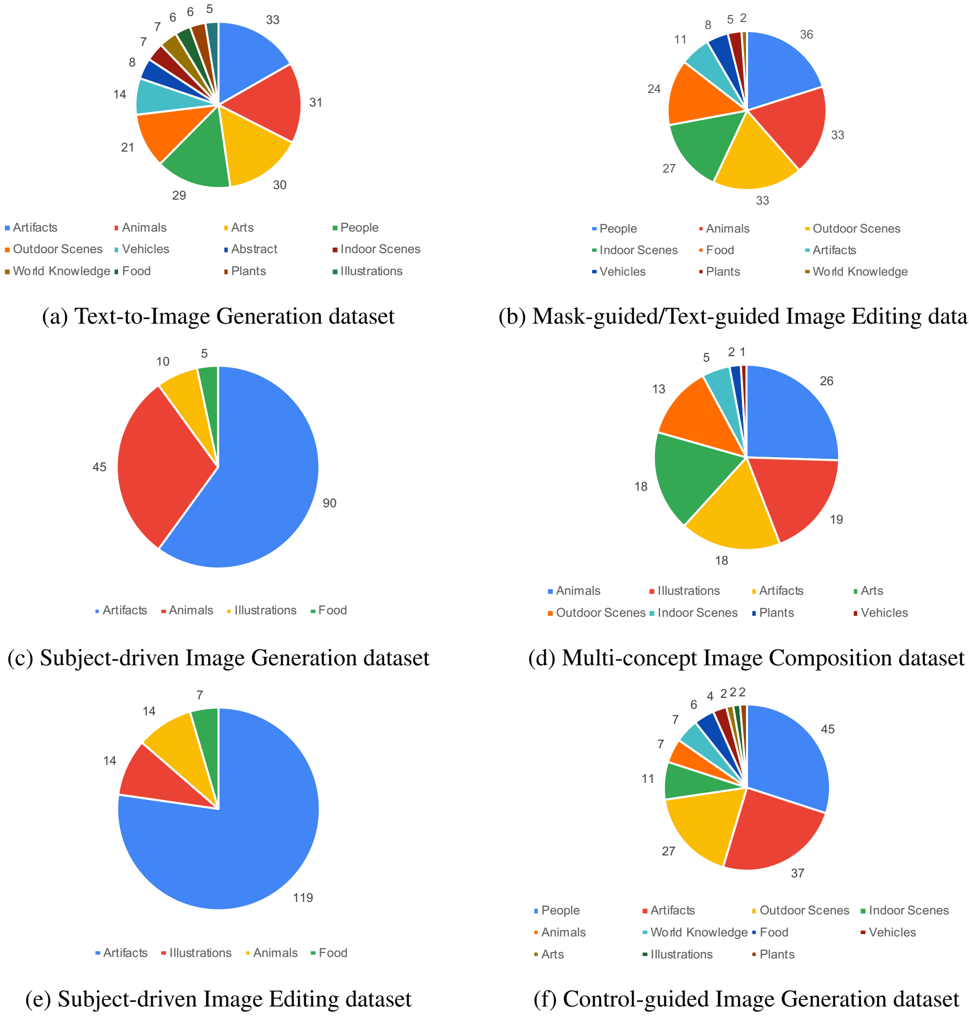
Figure 11: Rating examples on Control-guided Image Generation task.

- OutputA$_1$: `[1, 0.5]`. SC=1: The generated image perfectly described all the required attributes of the user prompt, and even work. PR=0.5: There are some missing details in the background. The details in the far-side are mostly blurred unnaturally.
- OutputB$_1$: `[1, 0.5]`. SC=1: The generated image perfectly described all the required attributes of the user prompt. PR=0.5: The details of golden gate bridge are mostly blurred unnaturally.
- OutputA$_2$: `[0, 0]`. SC=0: The output does not correspond to the controlled depth image. PR=0: Heavy distortion on the background and the man.
- OutputB$_2$: `[0, 0]`. SC=0: The meaning of the text cannot be obtained from the output. PR=0: Heavy distortion.

A.4 Dataset Information

Dataset Details.

Dataset Distribution.



(a) Text-to-Image Generation dataset

(b) Mask-guided/Text-guided Image Editing dataset

(c) Subject-driven Image Generation dataset

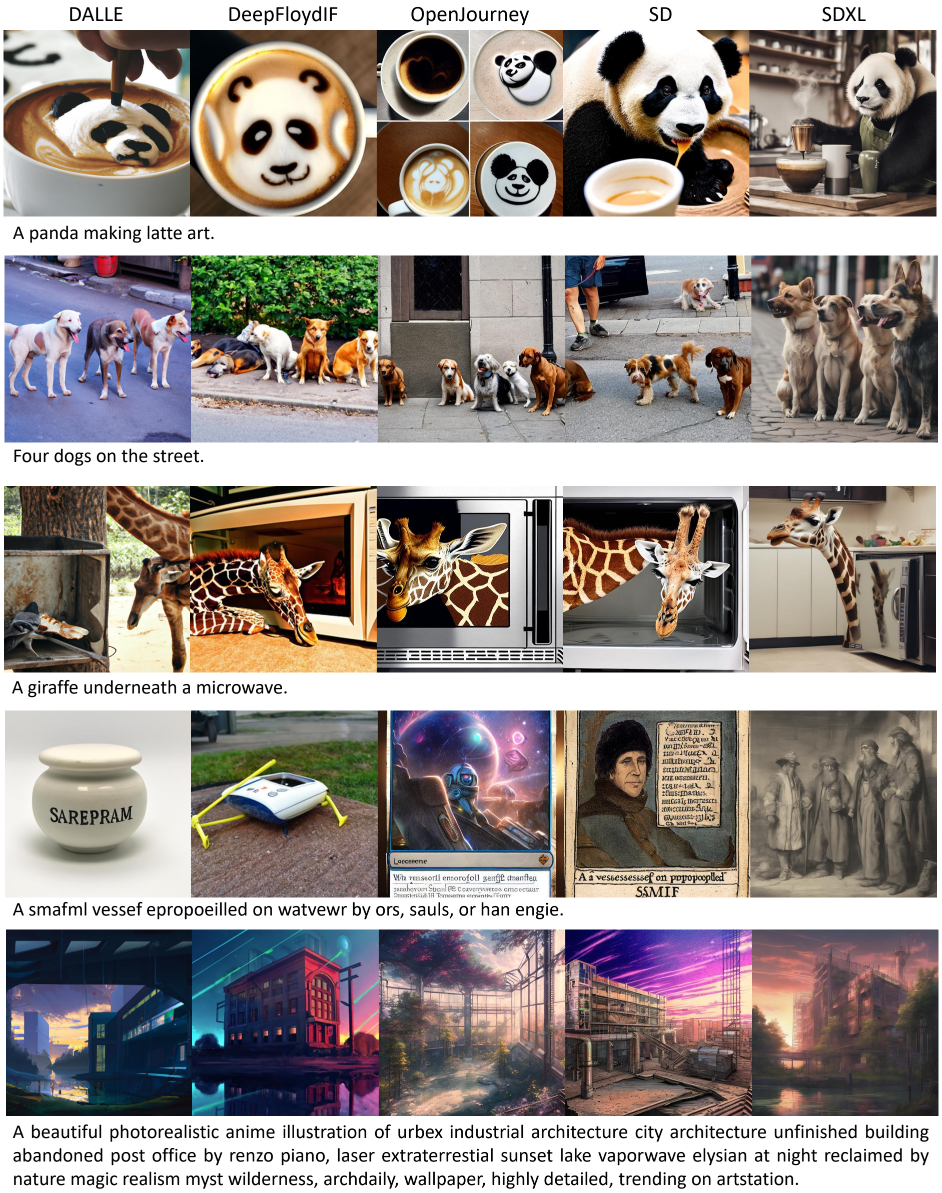
(d) Multi-concept Image Composition dataset

(e) Subject-driven Image Editing dataset

(f) Control-guided Image Generation dataset

Figure 12: Objects presented in each task's prompt text.

A.5 VISUALIZATION



A panda making latte art.

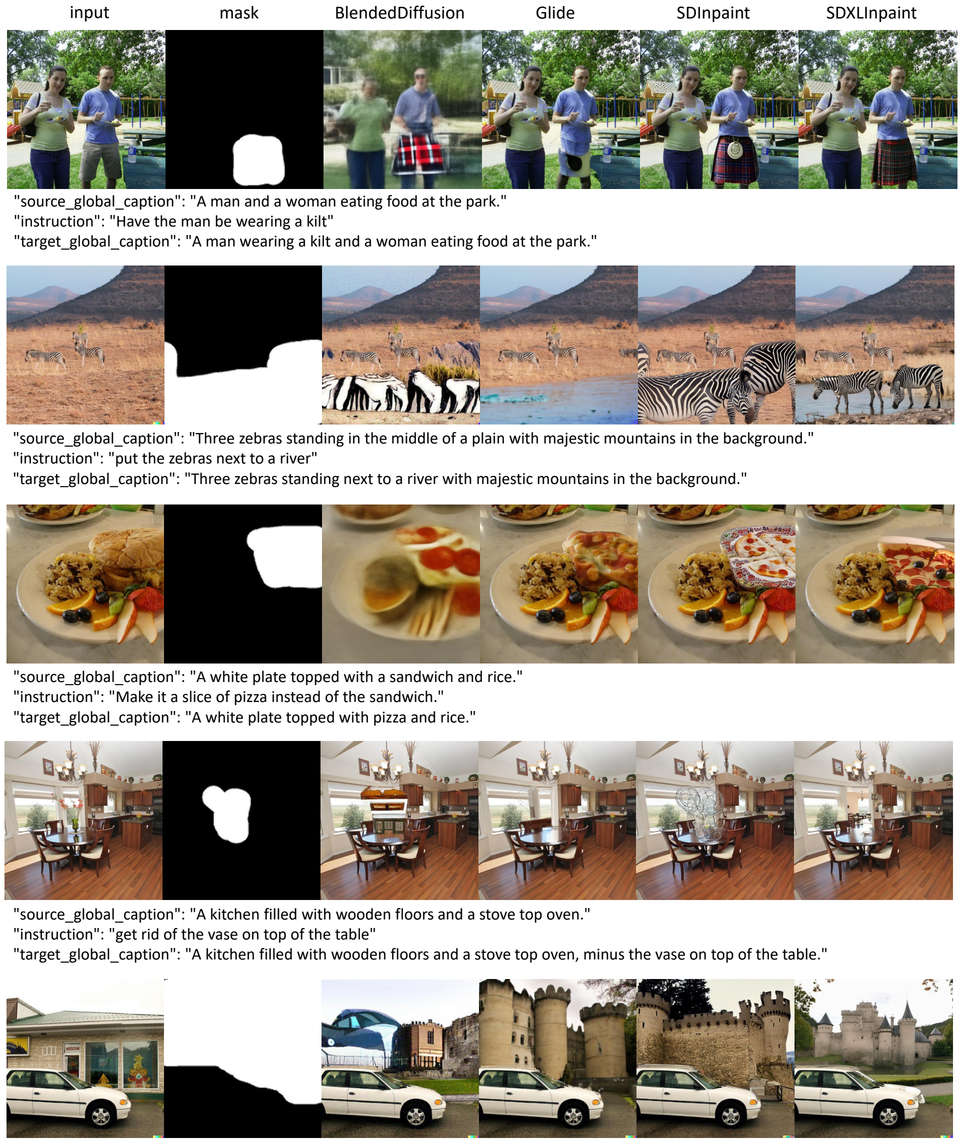
Four dogs on the street.

A giraffe underneath a microwave.

A smafml vessef epropoeilled on watvewr by ors, sauls, or han engie.

A beautiful photorealistic anime illustration of urbex industrial architecture city architecture unfinished building abandoned post office by renzo piano, laser extraterrestial sunset lake vaporwave elysian at night reclaimed by nature magic realism myst wilderness, archdaily, wallpaper, highly detailed, trending on artstation.

Figure 13: More samples from our Text-guided Image Generation dataset and ImagenHub outputs.



"source_global_caption": "A man and a woman eating food at the park."
"instruction": "Have the man be wearing a kilt"
"target_global_caption": "A man wearing a kilt and a woman eating food at the park."

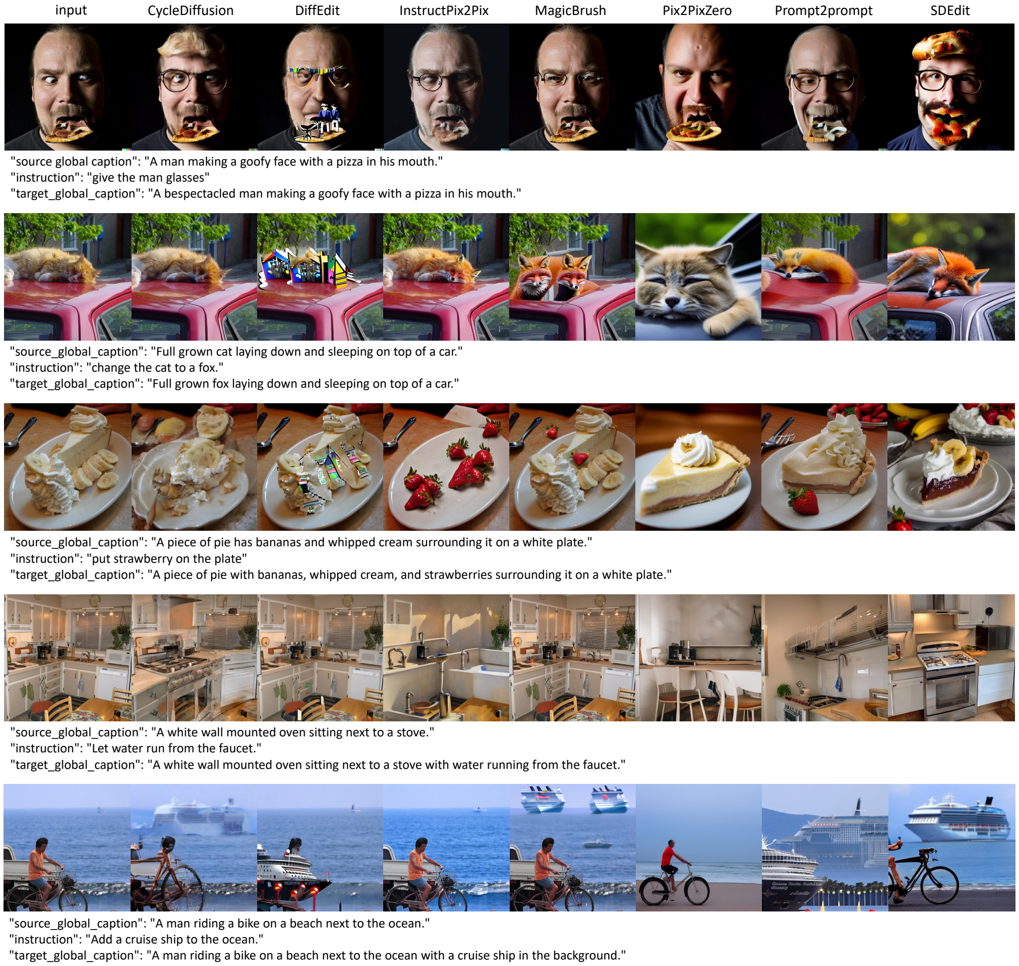
"source_global_caption": "Three zebras standing in the middle of a plain with majestic mountains in the background."
"instruction": "put the zebras next to a river"
"target_global_caption": "Three zebras standing next to a river with majestic mountains in the background."

"source_global_caption": "A white plate topped with a sandwich and rice."
"instruction": "Make it a slice of pizza instead of the sandwich."
"target_global_caption": "A white plate topped with pizza and rice."

"source_global_caption": "A kitchen filled with wooden floors and a stove top oven."
"instruction": "get rid of the vase on top of the table"
"target_global_caption": "A kitchen filled with wooden floors and a stove top oven, minus the vase on top of the table."

"source_global_caption": "Car parked in parking lot in front of a building."
"instruction": "edit the background by removing the museum and placing a castle"
"target_global_caption": "Car parked in front of a castle in a parking lot."

Figure 14: More samples from our Mask-guided Image Editing dataset and ImagenHub outputs.



"source global caption": "A man making a goofy face with a pizza in his mouth."
"instruction": "give the man glasses"
"target_global_caption": "A bespectacled man making a goofy face with a pizza in his mouth."

"source_global_caption": "Full grown cat laying down and sleeping on top of a car."
"instruction": "change the cat to a fox."
"target_global_caption": "Full grown fox laying down and sleeping on top of a car."

"source_global_caption": "A piece of pie has bananas and whipped cream surrounding it on a white plate."
"instruction": "put strawberry on the plate"
"target_global_caption": "A piece of pie with bananas, whipped cream, and strawberries surrounding it on a white plate."

"source_global_caption": "A white wall mounted oven sitting next to a stove."
"instruction": "Let water run from the faucet."
"target_global_caption": "A white wall mounted oven sitting next to a stove with water running from the faucet."

"source_global_caption": "A man riding a bike on a beach next to the ocean."
"instruction": "Add a cruise ship to the ocean."
"target_global_caption": "A man riding a bike on a beach next to the ocean with a cruise ship in the background."

Figure 15: More samples from our Text-guided Image Editing dataset and ImagenHub outputs.

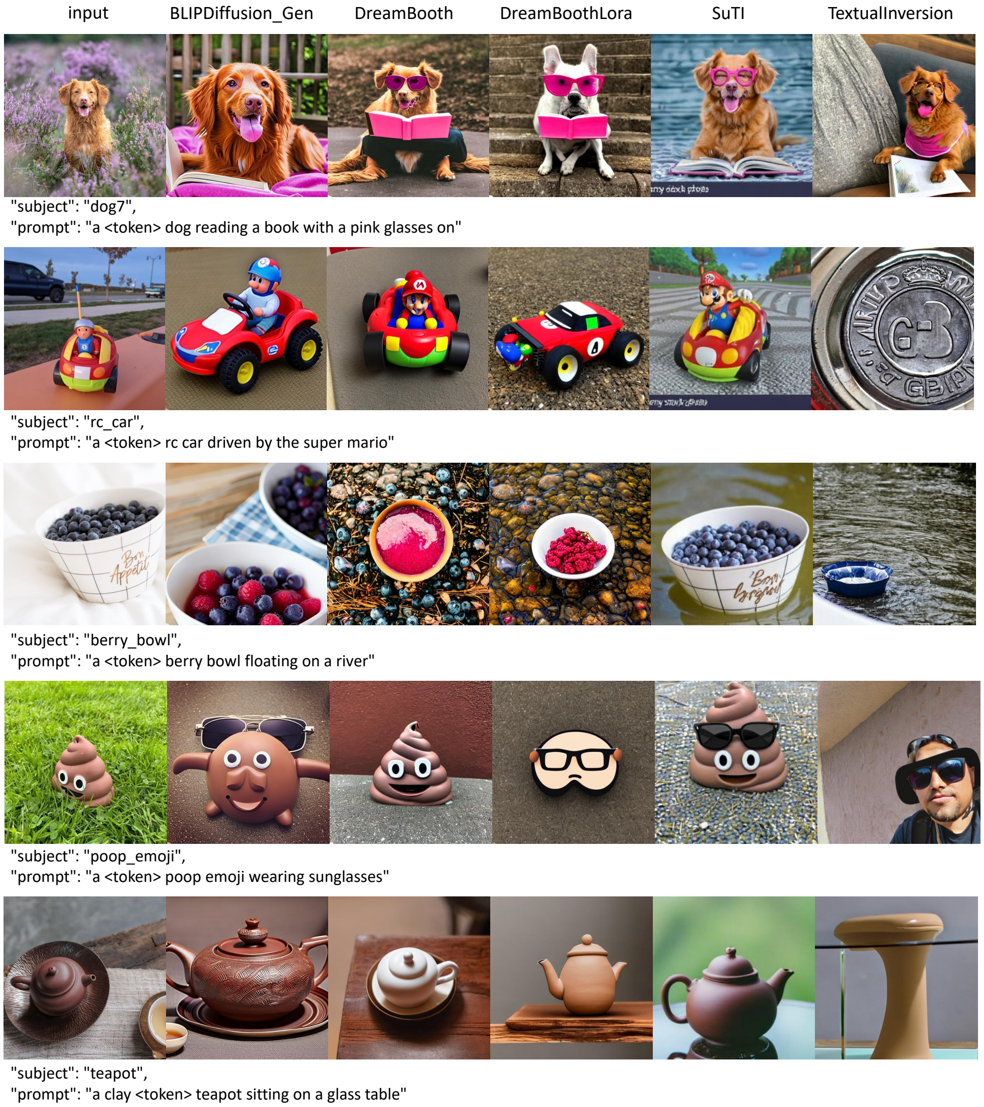

input
BLIPDiffusion_Gen
DreamBooth
DreamBoothLora
SuTI
TextualInversion
"subject": "dog7",
"prompt": "a <token> dog reading a book with a pink glasses on"
"subject": "rc_car",
"prompt": "a <token> rc car driven by the super mario"
"subject": "berry_bowl",
"prompt": "a <token> berry bowl floating on a river"
"subject": "poop_emoji",
"prompt": "a <token> poop emoji wearing sunglasses"
"subject": "teapot",
"prompt": "a clay <token> teapot sitting on a glass table"

Figure 16: More samples from our Subject-Driven Image Generation dataset and ImagenHub outputs.

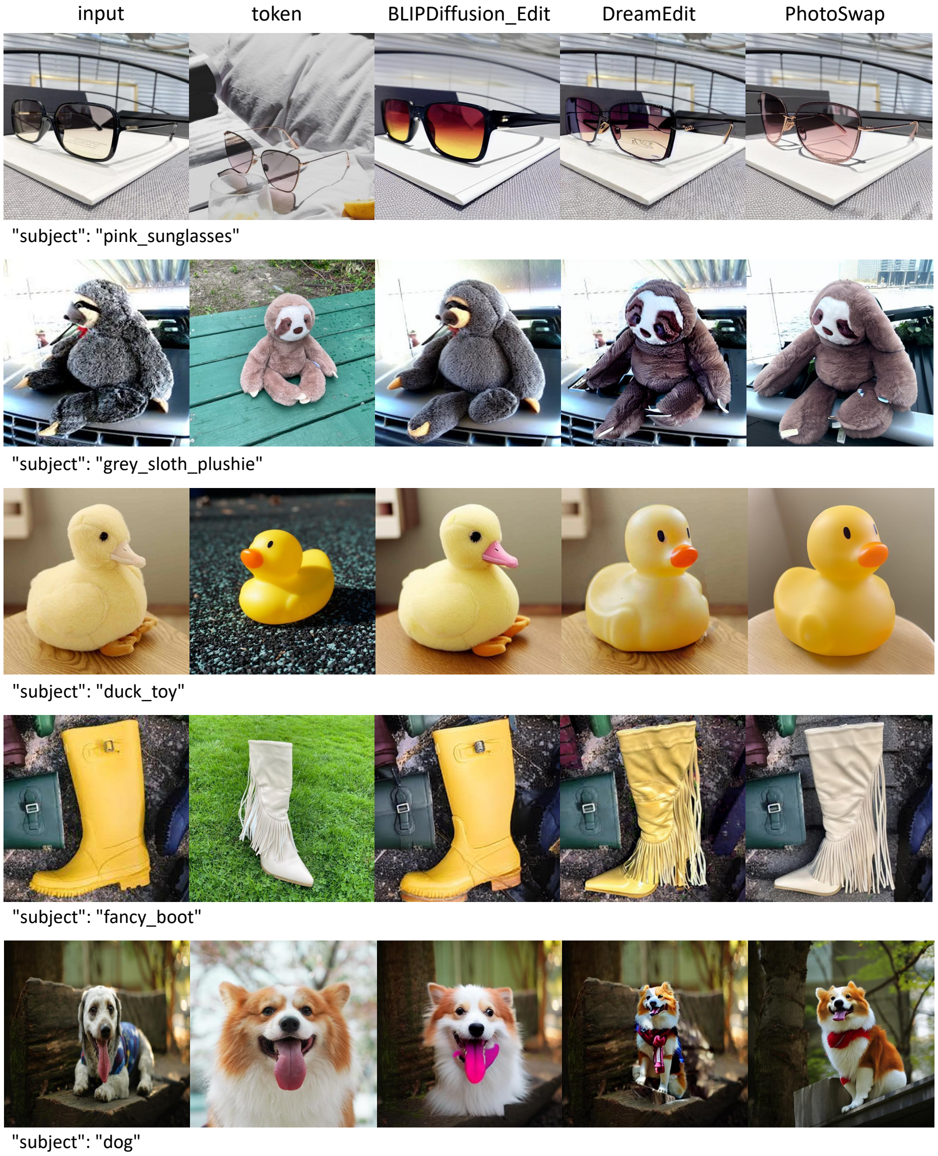
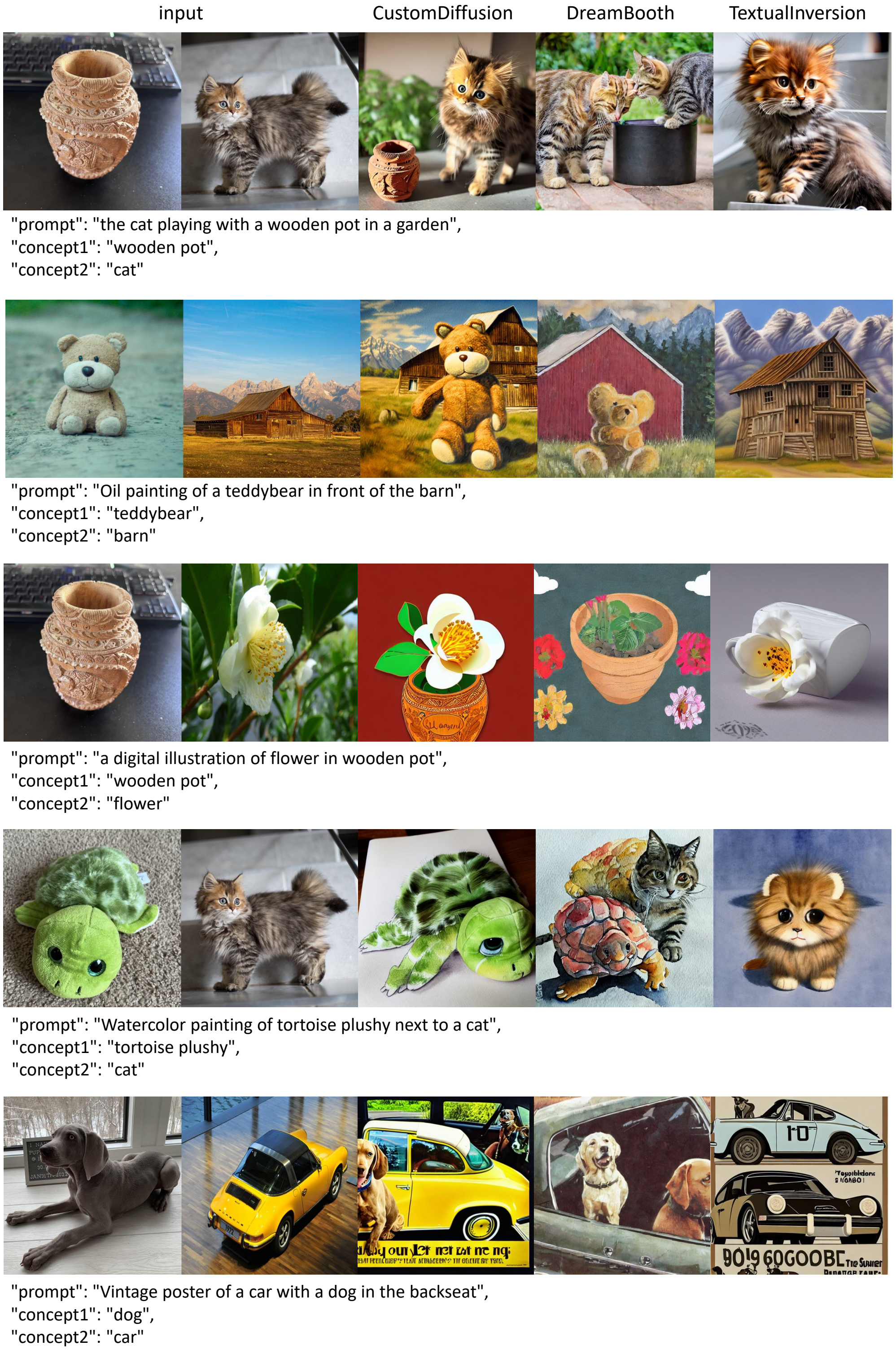


Figure 17: More samples from our Subject-Driven Image Editing dataset and ImagenHub outputs.



"prompt": "the cat playing with a wooden pot in a garden",
"concept1": "wooden pot",
"concept2": "cat"

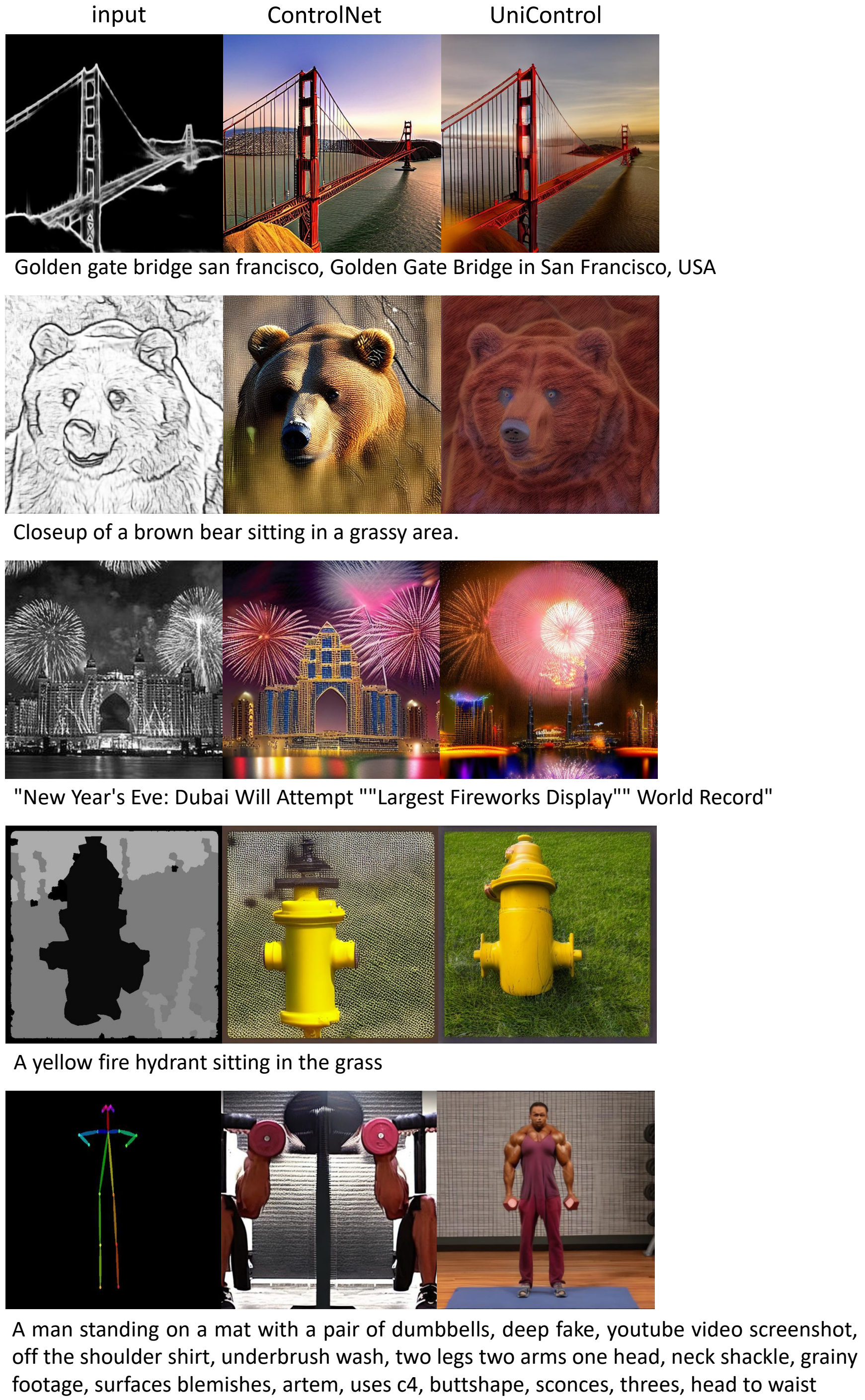
"prompt": "Oil painting of a teddybear in front of the barn",
"concept1": "teddybear",
"concept2": "barn"

"prompt": "a digital illustration of flower in wooden pot",
"concept1": "wooden pot",
"concept2": "flower"

"prompt": "Watercolor painting of tortoise plushy next to a cat",
"concept1": "tortoise plushy",
"concept2": "cat"

"prompt": "Vintage poster of a car with a dog in the backseat",
"concept1": "dog",
"concept2": "car"

Figure 18: More samples from our Multi-Concept Image Composition dataset and ImagenHub outputs.



Golden gate bridge san francisco, Golden Gate Bridge in San Francisco, USA

Closeup of a brown bear sitting in a grassy area.

"New Year's Eve: Dubai Will Attempt ""Largest Fireworks Display"" World Record"

A yellow fire hydrant sitting in the grass

A man standing on a mat with a pair of dumbbells, deep fake, youtube video screenshot, off the shoulder shirt, underbrush wash, two legs two arms one head, neck shackle, grainy footage, surfaces blemishes, artem, uses c4, buttshape, sconces, threes, head to waist

Figure 19: More samples from our Control-guided Image Generation dataset and ImagenHub outputs.

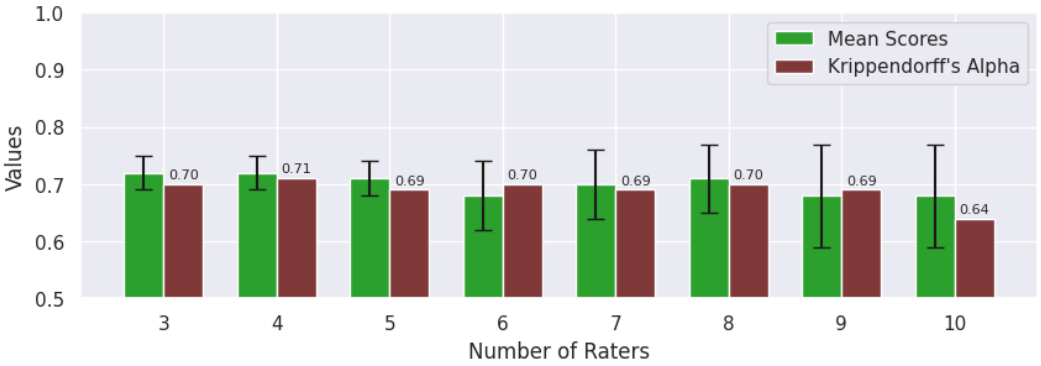


Figure 20: Mean scores of overall human rating and Krippendorff's Alpha for each number of raters on one model.

A.6 Human evaluation procedure

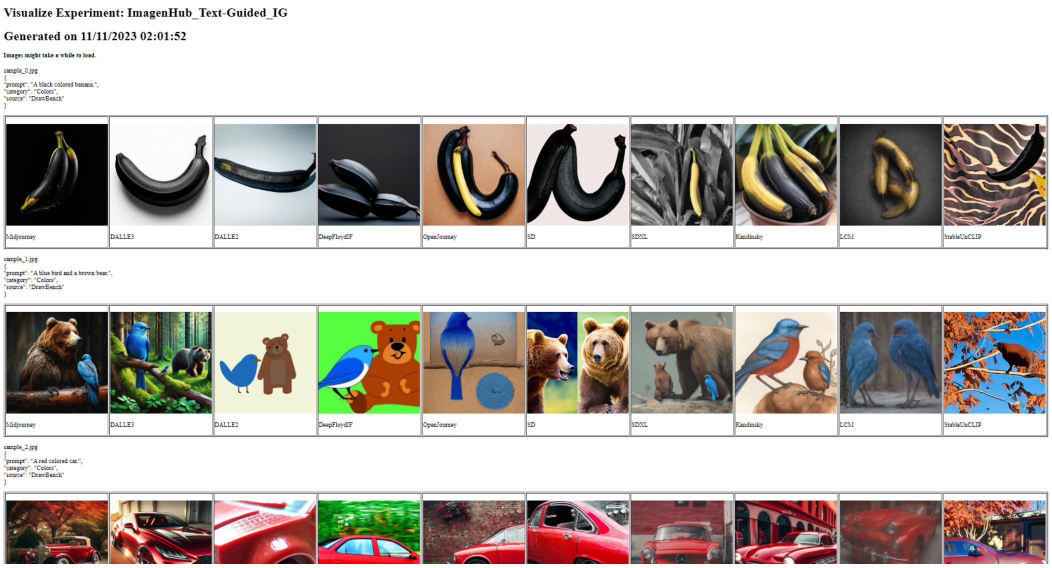
Prolific. In this work, we used the Prolific platform to receive human feedback on rating AI-generated images. We applied the following filter for worker requirements when creating the project: 1) The Worker's primary speaking language has to be English. 2) Worker must complete rating one set of images (around 150-200 images) in one go. We do that to ensure workers can fully understand the rating instructions, and each set of image is rated by the same person so we can perform Inter-rater Reliability Analysis across the whole set of the benchmark. Workers will rate each image in [SC, PQ], while SC in [0, 0.5, 1] and PQ in [0, 0.5, 1]. Instructions and images are hosted on a website. Workers are provided with detailed instructions and rating examples to assist their rating process. Workers will submit the responses in a tsv file. To validate the annotation quality, we selected a few (around 10-20) significant samples with obvious ratings for each task. We rated them by ourselves and then used them as a reference to determine the performance of annotators. Poor performance will be rejected.

Sample Size Consideration of Human Raters.

We studied the effect on the number of human raters. We recruited 10 human raters on Prolific to rate 15 samples generated using the Midjourney model. In Figure 20, the mean scores seem to remain relatively constant across the number of raters, with a slight increase at 4 raters and the highest mean score at 5 raters. The values for the mean scores are hovering around 0.70, as the error bar shows the standard deviation increases. On the other hand, Krippendorff's Alpha generally decreases as the number of raters increases. It starts at around 0.70 with 3 raters and has a noticeable drop at 10 raters to 0.64. We can observe that the mean score will be always consistent, while the reliability of that score as measured by Krippendorff's Alpha decreases slightly as more raters are involved, as more variance is introduced. To make our human evaluation protocol efficient, we picked 3 as the number of human raters.

A.7 VISUALIZATION TOOLS (IMAGEN MUSEUM)

Experiment Transparency. We are hosting the benchmarking results publicly. Thus showing the true performance of each model. Viewers can gain their insights from the result by looking at the actual results. Our framework encourages future researchers to release the human evaluation set generation results publicly. By standardizing the human evaluation protocol, human evaluation results would become far more convincing with the experiment transparency.



Visualize Experiment: ImagenHub_Text-Guided_IG

Generated on 11/11/2023 02:01:52

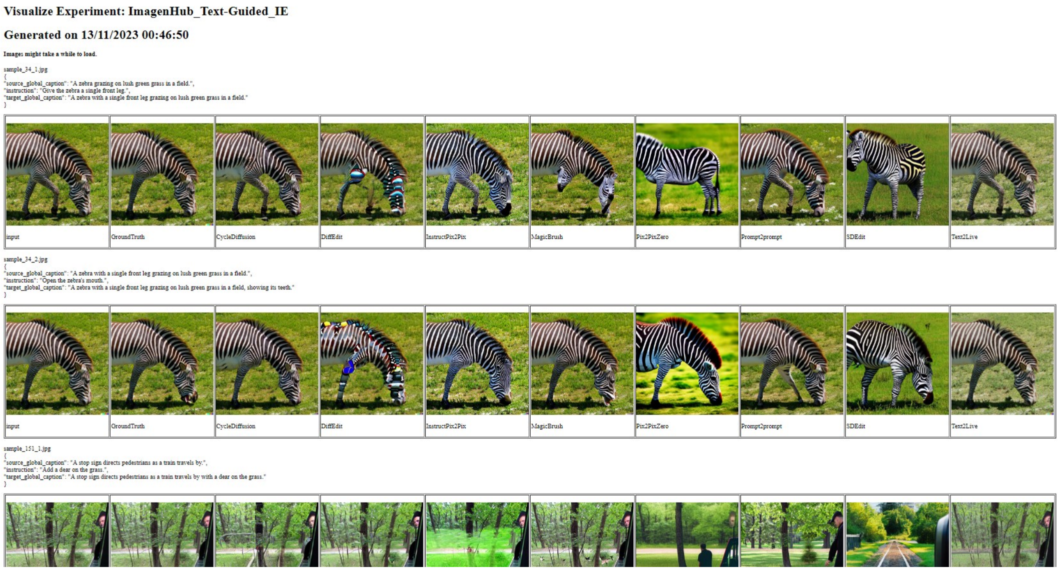
Images might take a while to load.

```
sample_0.jpg
{
"prompt": "A black colored banana.",
"category": "Colors",
"source": "DrawBench"
}
```

```
sample_1.jpg
{
"prompt": "A blue bird and a brown bear.",
"category": "Colors",
"source": "DrawBench"
}
```

```
sample_2.jpg
{
"prompt": "A red colored car.",
"category": "Colors",
"source": "DrawBench"
}
```

Figure 21: The webpage design of Imagen Museum (Text-Guided Image Generation page).



Visualize Experiment: ImagenHub_Text-Guided_IE

Generated on 13/11/2023 00:46:50

Images might take a while to load.

```
sample_34_1.jpg
{
"source_global_caption": "A zebra grazing on lush green grass in a field.",
"instruction": "Give the zebra a single front leg.",
"target_global_caption": "A zebra with a single front leg grazing on lush green grass in a field."
}
```

```
sample_34_2.jpg
{
"source_global_caption": "A zebra with a single front leg grazing on lush green grass in a field.",
"instruction": "Open the zebra's mouth.",
"target_global_caption": "A zebra with a single front leg grazing on lush green grass in a field, showing its teeth."
}
```

```
sample_151_1.jpg
{
"source_global_caption": "A stop sign directs pedestrians as a train travels by.",
"instruction": "Add a dear on the grass.",
"target_global_caption": "A stop sign directs pedestrians as a train travels by with a dear on the grass."
}
```

Figure 22: The webpage design of Imagen Museum (Text-Guided Image Editing page).

Please refer to https://github.com/ChromAIca/ChromAIca.github.io for the visualization results.

A.8 ADDING NEW MODELS TO OUR FRAMEWORK.

Third parties are welcome to use our provided tools and frameworks for their work. Here is a quick walkthrough of how a third-party member can extend the framework to support their own model's inference. We use the Text-Guided Image Generation (Text-To-Image) task as an example for the sake of simplicity.

The `infermodel` class is designed to have the following two methods:

- `__init__(args)` for class initialization.
- `infer_one_image(args)` to produce 1 image output. Please try to set the seed as 42.

In that case, you will add a new file in `imagen_hub/infermodels` folder. `imagen_hub/infermodels/awesome_model.py`

Then a line can be added in `imagen_hub/infermodels/__init__.py`:

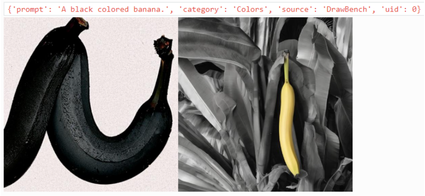
And modify the template config.yml file and add your own model.

Finally run

Please refer to https://imagenhub.readthedocs.io/en/latest/Guidelines/custommodel.html for details.

A.9 IMAGENHUB AS AN INFERENCE LIBRARY.

Custom inference of multiple models.



```
{'prompt': 'A black colored banana.', 'category': 'Colors', 'source': 'DrawBench', 'uid': 0}
```

Figure 23: Image generated in this custom inference example.

Evaluate images with autometrics.

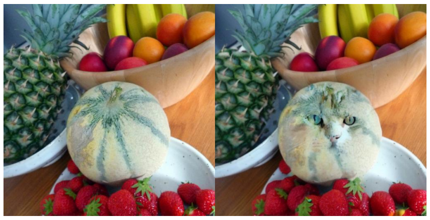


Figure 24: Image evaluated in this autometrics example.

Please refer to https://imagenhub.readthedocs.io/en/latest/Guidelines/deepdive.html for details.