

## A Evaluating Text-to-Vision generation models with GENERATE ANY SCENE

### A.1 Experiment Settings

**Models.** We conduct experiments on 12 *Text-to-image* models [54, 50, 22, 51, 52, 55, 56, 57, 58, 3], 9 *Text-to-Video* models [63, 83, 62, 60, 61, 64, 67, 66, 65], and 5 *Text-to-3D* models [68, 71, 69, 4, 70].

- For *Text-to-Image* generation, we select a range of open-source models, including those utilizing UNet backbones, such as *DeepFloyd IF* [54], *SDv2.1* [22], *SDXL* [50], *Playground v2.5* [51], and *Wuerstchen v2* [52], as well as models with DiT backbones, including *SD3 Medium* [55], *PixArt- $\alpha$*  [56], *PixArt- $\Sigma$*  [57], *FLUX.1-schnell* [58], *FLUX.1-dev* [58], and *FLUX 1*. Closed-source models, such as *DaLL-E 3* [3] and *FLUX1.1 PRO* [58], are also assessed to ensure a comprehensive comparison. All models are evaluated at a resolution of  $1024 \times 1024$  pixels.
- For *Text-to-Video* generation, we select nine open-source models: *ModelScope* [63], *ZeroScope* [83], *Text2Video-Zero* [62], *CogVideoX-2B* [66], *VideoCrafter2* [65], *AnimateLCM* [61], *AnimateDiff* [60], *FreeInit* [64], and *Open-Sora 1.2* [67]. We standardize the frame length to 16 across all video models for fair comparisons.
- For *Text-to-3D* generation, we evaluate five recently proposed models: *SJC* [69], *Dream-Fusion* [68], *Magic3D* [71], *Latent-NeRF* [70], and *ProlificDreamer* [4]. We employ the implementation and configurations provided by ThreeStudio [84] and generate videos by rendering from 120 viewpoints. To accelerate inference, we omit the refinement stage. For *Magic3D* and *DreamFusion*, we respectively use *DeepFloyd IF* and *SDv2.1* as their 2D backbones.

**Metrics.** Across all *Text-to-Vision* generation tasks, we use *Clip Score* [49] (semantic similarity), *VQA Score* [37] (faithfulness), *TIFA Score* [23, 31] (faithfulness), *Pick Score* [85] (human preference), and *ImageReward Score* [86] (human preference) as general metrics:

- *Clip Score*: Assesses semantic similarity between images and text.
- *VQA Score* and *TIFA Score*: Evaluate faithfulness by generating question-answer pairs and measuring answer accuracy from images.
- *Pick Score* and *ImageReward Score*: Capture human preference tendencies.

We also use metrics in VBench [87] to evaluate *Text-to-Video* generation models on fine-grained dimensions, such as consistency and dynamics, providing detailed insights into video performance.

For *Text-to-Video* generation and *Text-to-3D* generation tasks:

- We calculate *Clip Score*, *Pick Score*, and *ImageReward Score* on each frame, then average these scores across all frames to obtain an overall video score.
- For *VQA Score* and *TIFA Score*, we handle *Text-to-Video* generation and *Text-to-3D* generation tasks differently:
  - In *Text-to-Video* generation tasks, we uniformly sample four frames from the 16-frame sequence and arrange them in a  $2 \times 2$  grid image.
  - For *Text-to-3D* generation tasks, we render images at 45-degree intervals from nine different viewpoints and arrange them in a  $3 \times 3$  grid.

This sampling approach optimizes inference speed without affecting score accuracy [37].

**Synthetic captions.** We evaluate our *Text-to-Image* generation and *Text-to-Video* generation models on 10K randomly generated captions, with scene graph complexity ranging from 3 to 12 and scene attributes from 0 to 5, using unrestricted metadata. The captions exhibit an average graph degree of 1.15, with values spanning from 0.0 to 0.8. The mean number of connected components per scene graph is 3.51, ranging from 1 to 11. For *Text-to-3D* generation models, due to their limitations in handling complex captions and time-intensive generation, we restrict scene graph complexity to 1-3, scene attributes to 0-2, and evaluate on 1K captions.

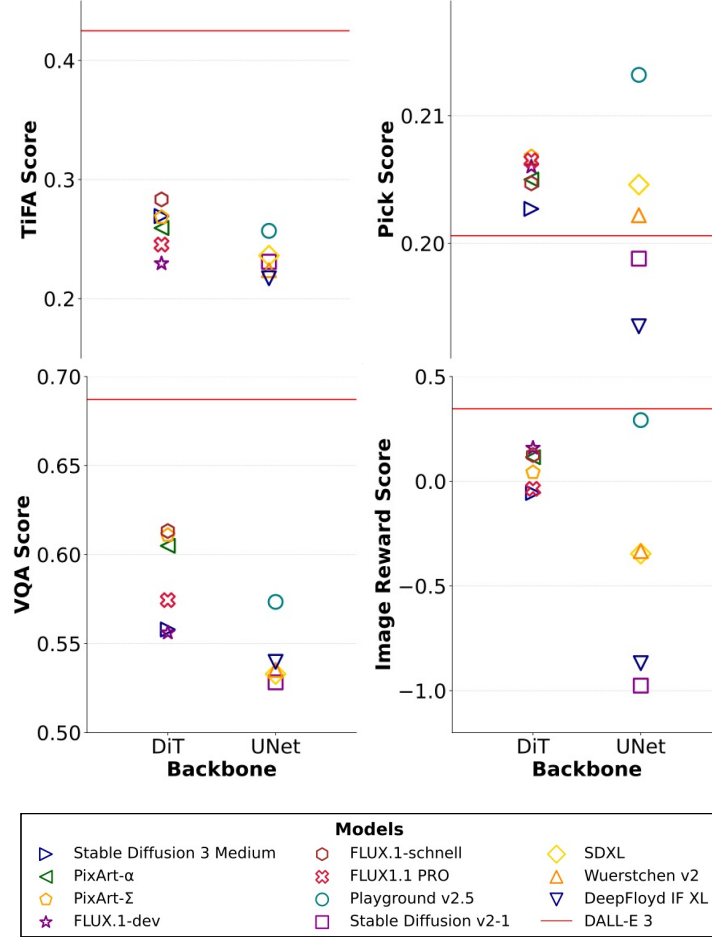


Figure 7: Comparative evaluation of *Text-to-Image* generation models across different backbones (DiT and UNet) using multiple metrics: *TIFA Score*, *Pick Score*, *VQA Score*, and *ImageReward Score*.

## A.2 Overall results

We evaluate *Text-to-Image* generation, *Text-to-Video* generation, and *Text-to-3D* generation models on GENERATE ANY SCENE.

Table 3: Overall performance of *Text-to-Image* generation models over 10K GENERATE ANY SCENE captions. <sup>†</sup>Evaluated on a 1K caption subset due to inference cost constraints.

| Model                          | clip score | pick score | vqa score | tifa score | image reward score |
|--------------------------------|------------|------------|-----------|------------|--------------------|
| Playground v2.5 [51]           | 0.2581     | 0.2132     | 0.5734    | 0.2569     | 0.2919             |
| Stable Diffusion v2-1 [22]     | 0.2453     | 0.1988     | 0.5282    | 0.2310     | -0.9760            |
| SDXL [50]                      | 0.2614     | 0.2046     | 0.5328    | 0.2361     | -0.3463            |
| Wuerstchen v2 [52]             | 0.2448     | 0.2022     | 0.5352    | 0.2239     | -0.3339            |
| DeepFloyd IF XL [54]           | 0.2396     | 0.1935     | 0.5397    | 0.2171     | -0.8687            |
| Stable Diffusion 3 Medium [55] | 0.2527     | 0.2027     | 0.5579    | 0.2693     | -0.0557            |
| PixArt-α [56]                  | 0.2363     | 0.2050     | 0.6049    | 0.2593     | 0.1149             |
| PixArt-Σ [57]                  | 0.2390     | 0.2068     | 0.6109    | 0.2683     | 0.0425             |
| FLUX.1-dev [58]                | 0.2341     | 0.2060     | 0.5561    | 0.2295     | 0.1588             |
| FLUX.1-schnell [58]            | 0.2542     | 0.2047     | 0.6132    | 0.2833     | 0.1251             |
| FLUX1.1 PRO [58] <sup>†</sup>  | 0.2315     | 0.2065     | 0.5744    | 0.2454     | -0.0361            |
| Dalle-3 [3]                    | 0.2518     | 0.2006     | 0.6871    | 0.4249     | 0.3464             |

*Text-to-Image* generation results. (Figure 7, Table 3)



1. DiT-backbone models outperform UNet-backbone models on *VQA Score* and *TIFA Score*, indicating greater faithfulness and comprehensiveness to input captions.
2. Despite using a UNet architecture, *Playground v2.5* achieves higher *Pick Score* and *ImageReward Score* scores than other open-source models. We attribute this to *Playground v2.5*'s alignment with human preferences achieved during training.
3. The closed-source model *DaLL-E 3* maintains a significant lead in *VQA Score*, *TIFA Score*, and *ImageReward Score*, demonstrating strong faithfulness and alignment with captions across generated content.

Text-to-Video generation results. (Table 4, 5)

Table 4: Overall performance of open-source *Text-to-Video generation* models over 10K GENERATE ANY SCENE captions. Red Cell is the highest score. Yellow Cell is the second highest score.† Close-source models are evaluated on a 1K caption subset due to high inference cost.

| Model                | clip score | pick score | image reward score | VQA score | TiFA score |
|----------------------|------------|------------|--------------------|-----------|------------|
| VideoCraft2 [65]     | 0.2398     | 0.1976     | -0.4202            | 0.5018    | 0.2466     |
| AnimateLCM [61]      | 0.2450     | 0.1987     | -0.5754            | 0.4816    | 0.2176     |
| AnimateDiff [60]     | 0.2610     | 0.1959     | -0.7301            | 0.5255    | 0.2208     |
| Open-Sora 1.2 [67]   | 0.2259     | 0.1928     | -0.6277            | 0.5519    | 0.2414     |
| FreeInit [64]        | 0.2579     | 0.1950     | -0.9335            | 0.5123    | 0.2047     |
| ModelScope [63]      | 0.2041     | 0.1886     | -1.9172            | 0.3840    | 0.1219     |
| Text2Video-Zero [62] | 0.2539     | 0.1933     | -1.2050            | 0.4753    | 0.1952     |
| CogVideoX-2B [66]    | 0.2038     | 0.1901     | -1.2301            | 0.4585    | 0.1997     |
| ZeroScope [83]       | 0.2289     | 0.1933     | -1.1599            | 0.4892    | 0.2388     |
| KLING 1.6 [88]†      | 0.2215     | 0.1985     | -0.3419            | 0.5307    | 0.2802     |
| Wanx 2.1 [89]†       | 0.2308     | 0.1969     | -0.1418            | 0.5970    | 0.3328     |

Table 5: Overall performance of open-source *Text-to-Video generation* models over 10K GENERATE ANY SCENE captions with VBench metrics. Red Cell is the highest score. Blue Cell is the lowest score.

| Model           | subject consistency | background consistency | motion smoothness | dynamic degree | aesthetic quality | imaging quality |
|-----------------|---------------------|------------------------|-------------------|----------------|-------------------|-----------------|
| Open-Sora 1.2   | 0.9964              | 0.9907                 | 0.9973            | 0.0044         | 0.5235            | 0.6648          |
| Text2Video-Zero | 0.8471              | 0.9030                 | 0.8301            | 0.9999         | 0.4889            | 0.7018          |
| VideoCraft2     | 0.9768              | 0.9688                 | 0.9833            | 0.3556         | 0.5515            | 0.6974          |
| AnimateDiff     | 0.9823              | 0.9733                 | 0.9859            | 0.1406         | 0.5427            | 0.5830          |
| FreeInit        | 0.9581              | 0.9571                 | 0.9752            | 0.4440         | 0.5200            | 0.5456          |
| ModelScope      | 0.9795              | 0.9831                 | 0.9803            | 0.1281         | 0.3993            | 0.6494          |
| AnimateLCM      | 0.9883              | 0.9802                 | 0.9887            | 0.0612         | 0.6323            | 0.6977          |
| CogVideoX-2B    | 0.9583              | 0.9602                 | 0.9823            | 0.4980         | 0.4607            | 0.6098          |
| ZeroScope       | 0.9814              | 0.9811                 | 0.9919            | 0.1670         | 0.4582            | 0.6782          |

1. Open-source text-to-video models face challenges in balancing dynamics and consistency (Table 5). This is especially evident in *Open-Sora 1.2*, which achieves high consistency but minimal dynamics, and *Text2Video-Zero*, which excels in dynamics but suffers from frame inconsistency.
2. All models exhibit negative *ImageReward Score* (Table 4), suggesting a lack of human-preferred visual appeal in the generated content, even in cases where certain models demonstrate strong semantic alignment.
3. As expected, SOTA close-source text-to-video models outperform others overall, particularly in image reward, VQA score, and TIFA score. This indicates their superior alignment with human preferences, as well as stronger faithfulness and compositional capabilities in generation.

4. Among open-source models, *VideoCrafter2* strikes a balance across key metrics, leading in human-preference alignment, faithfulness, consistency, and dynamic.

#### Text-to-3D generation results. (Table 6)

Table 6: Overall performance of *Text-to-3D generation* models over 1K GENERATE ANY SCENE captions. <sup>†</sup>Evaluated on a 100 caption subset due to high inference cost.

| Model                     | clip score    | pick score    | vqa score     | tifa score    | image reward score |
|---------------------------|---------------|---------------|---------------|---------------|--------------------|
| Latent-NeRF [70]          | 0.2115        | 0.1910        | 0.4767        | 0.2216        | -1.5311            |
| DreamFusion-sd [68]       | 0.1961        | 0.1906        | 0.4421        | 0.1657        | -1.5582            |
| Magic3D-sd [71]           | 0.1947        | 0.1903        | 0.4193        | 0.1537        | -1.6327            |
| SJC [69]                  | 0.2191        | 0.1915        | 0.5015        | 0.2563        | -1.4370            |
| DreamFusion-IF [68]       | 0.1828        | 0.1857        | 0.3872        | 0.1416        | -1.9353            |
| Magic3D-IF [71]           | 0.1919        | 0.1866        | 0.4039        | 0.1537        | -1.8465            |
| ProlificDreamer [4]       | 0.2125        | <b>0.1940</b> | <b>0.5411</b> | 0.2704        | -1.2774            |
| Meshy-4 [90] <sup>†</sup> | <b>0.2163</b> | 0.1922        | 0.5290        | <b>0.2908</b> | <b>-1.0496</b>     |

1. Among open-source models, *ProlificDreamer* outperforms other models, particularly in *ImageReward Score*, *VQA Score* and *TIFA Score*.
2. All models receive negative *ImageReward Score* scores, highlighting a significant gap between human preference and current *Text-to-3D generation* generation capabilities.
3. Meshy-4 demonstrates overall superior performance compared to all open-source models, especially in terms of *Clip Score*, *TIFA Score* and *ImageReward Score*, reflecting its strengths in semantic generation and human preference alignment.

### A.3 More Analysis with GENERATE ANY SCENE

With GENERATE ANY SCENE, we can generate infinitely diverse and highly controllable captions. Using GENERATE ANY SCENE, we conduct several analyses to provide insights into the performance of today’s *Text-to-Vision generation* models.

#### A.3.1 Performance analysis across caption properties

In this section, we delve into how model performance varies with respect to distinct properties of GENERATE ANY SCENE captions. While GENERATE ANY SCENE is capable of generating an extensive diversity of captions, these outputs inherently differ in key characteristics that influence model evaluation. Specifically, we examine three properties of the caption: Commonsense, Perplexity, and Scene Graph Complexity (captured as the number of elements in the captions). These properties are critical in understanding how different models perform across a spectrum of linguistic and semantic challenges presented by captions with varying levels of coherence, plausibility, and compositional richness.

**Perplexity. (Figure 8)** Perplexity is a metric used to measure a language model’s unpredictability or uncertainty in generating a text sequence. A higher perplexity value indicates that the sentences are less coherent or less likely to be generated by the model.

As shown in Figure 8, From left to right, when perplexity increases, indicating that the sentences become less reasonable and less typical of those generated by a language model, we observe no clear or consistent trends across all models and metrics. This suggests that the relationship between perplexity and model performance varies depending on the specific model and evaluation metric.

**Commonsense. (Figure 9)** Commonsense is an inherent property of text. We utilize the Vera Score [91], a metric generated by a fine-tuned LLM to evaluate the text’s commonsense level.

As shown in Figure 9, from left to right, as the Vera Score increases—indicating that the captions exhibit greater commonsense reasoning—we observe a general improvement in performance across

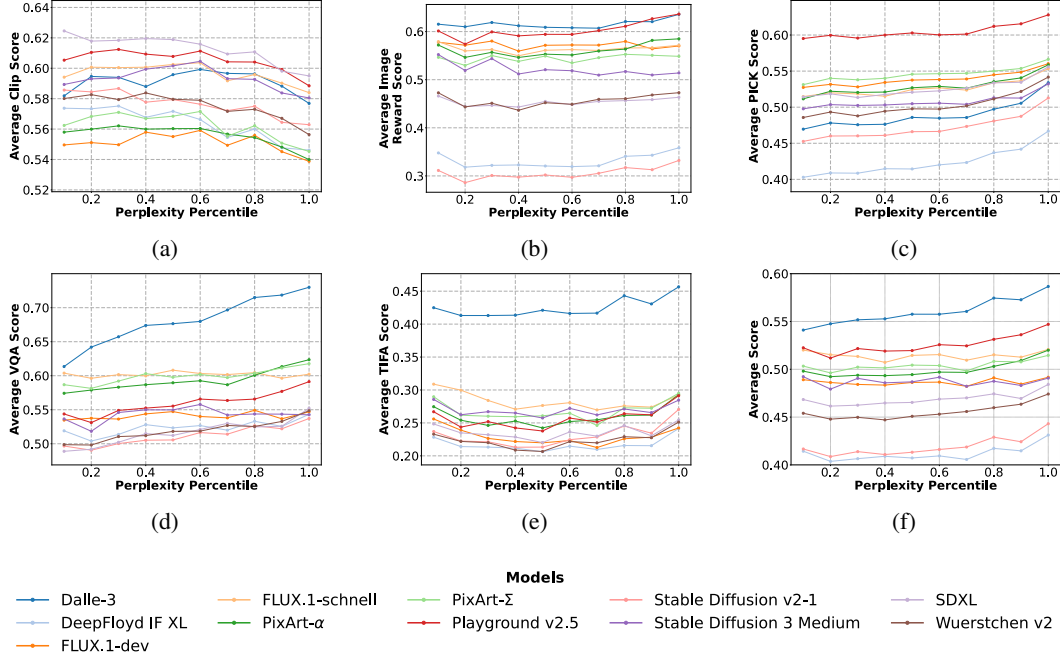


Figure 8: Average performance of models across different percentiles of perplexity of captions, evaluated on various metrics. From left to right, the perplexity decreases, indicating captions that are progressively more reasonable and easier for the LLM to generate.

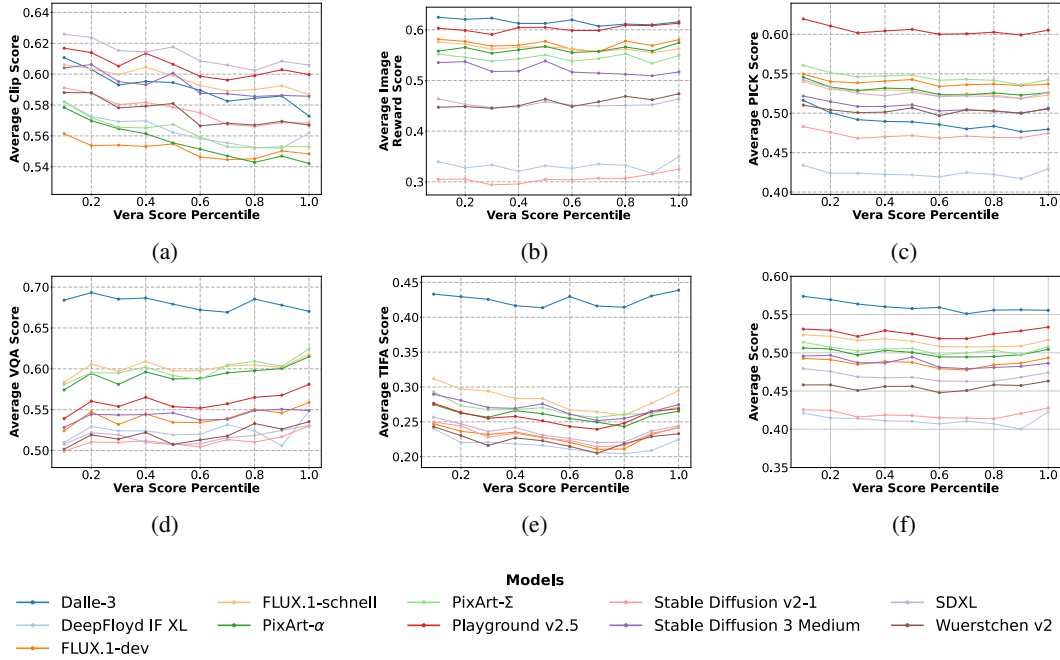


Figure 9: Average performance of models across different percentiles of Vera Score for captions, evaluated on various metrics. From left to right, the Vera Score decreases, indicating captions that exhibit less commonsense reasoning and are more likely to describe implausible scenes.

716 all metrics and models, except for *Clip Score*. This trend underscores the correlation between  
 717 commonsense-rich captions and enhanced model performance.

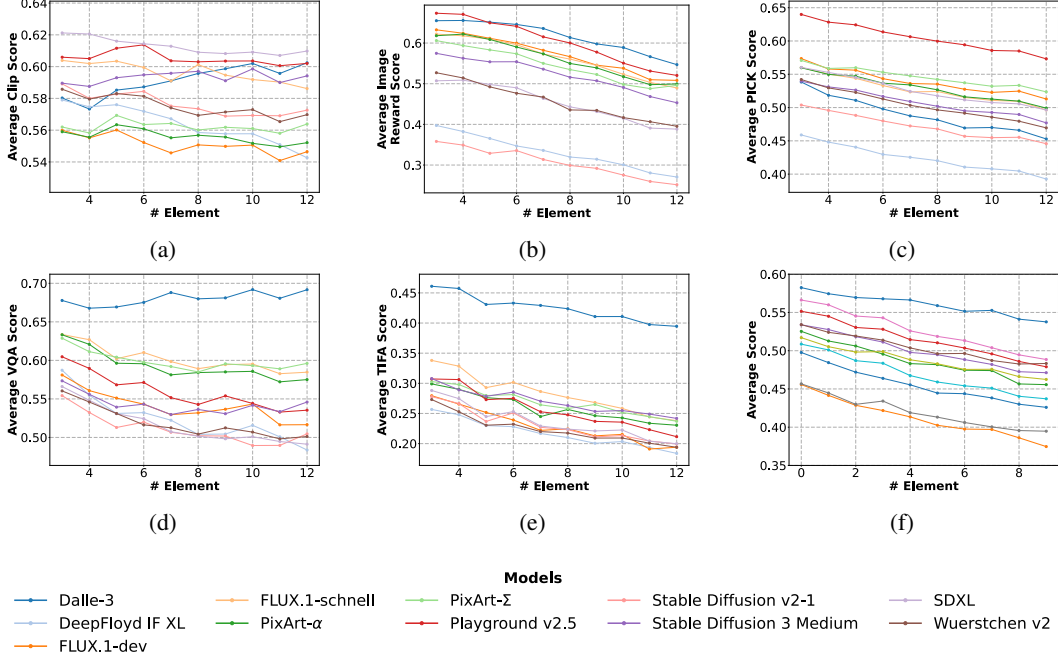


Figure 10: Average performance of models across different numbers of elements (objects + attributes + relations) in the scene graph (complexity of the scene graph) of the captions, evaluated on various metrics. From left to right, as the number of elements (complexity) increases, the scene graphs become more complicated and compositional.

718 **Element Numbers (Complexity of Scene Graph).** (Figure 10) Finally, we evaluate model  
719 performance across total element numbers in the captions, which represent the complexity of scene  
720 graphs (objects + attributes + relations).

721 From left to right, the complexity of scene graphs becomes higher, reflecting more compositional and  
722 intricate captions. Across most metrics and models, we observe a noticeable performance decline  
723 as the scene graphs become more complex. However, an interesting exception is observed in the  
724 performance of *DaLL-E 3*. Unlike other models, *DaLL-E 3* performs exceptionally well on *VQA Score*  
725 and *TIFA Score*, particularly on *VQA Score*, where it even shows a slight improvement as  
726 caption complexity increases. This suggests that *DaLL-E 3* may have a unique capacity to handle  
727 complex and compositional captions effectively.

### 728 A.3.2 Analysis on different metrics

729 Compared with most LLM and VLM benchmarks that use multiple-choice questions and accuracy as  
730 metrics. There is no universal metric in evaluating *Text-to-Vision generation* models. Researchers  
731 commonly used model-based metrics like *Clip Score*, *VQA Score*, etc. Each of these metrics is created  
732 and fine-tuned for different purposes with bias. Therefore, we also analysis on different metrics.

733 ***Clip Score* isn't a universal metric.** *Clip Score* is one of the most widely used metrics in *Text-*  
734 *to-Vision generation* for evaluating the alignment between visual content and text. However, our  
735 analysis reveals that *Clip Score* is not a perfect metric and displays some unusual trends. For instance,  
736 as shown in Figures 8, 9, and 10, we compute the perplexity across 10K captions used in our study,  
737 where higher perplexity indicates more unpredictable or disorganized text. Interestingly, unlike other  
738 metrics, *Clip Score* decreases as perplexity lowers, suggesting that *Clip Score* tends to favor more  
739 disorganized text. This behavior is counterintuitive and highlights the potential limitations of using  
740 *Clip Score* as a robust alignment metric.

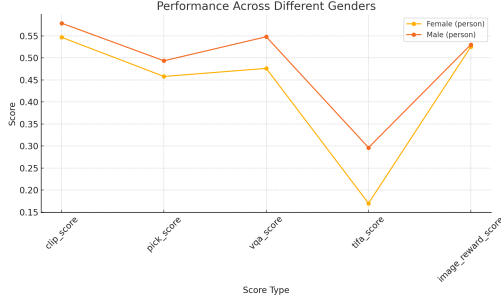


Figure 11: Average performance scores of all models across different genders evaluated using various metrics.

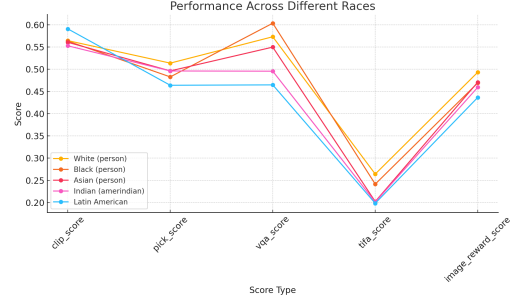


Figure 12: Average performance scores of all models across different races evaluated using various metrics.

**Limitations of human preference-based metrics.** We use two metrics fine-tuned using human preference data: *Pick Score* and *ImageReward Score*. However, we found that these metrics exhibit a strong bias toward the data on which they were fine-tuned. For instance, as shown in Table 3, *Pick Score* assigns similar scores across all models, failing to provide significant differentiation or meaningful insights into model performance. In contrast, *ImageReward Score* demonstrates clearer preferences, favoring models such as *DaLL-E 3* and *Playground v2.5*, which incorporated human-alignment techniques during their training. However, this metric shows a significant drawback: it assigns disproportionately large negative scores to models like *SDv2.1*, indicating a potential over-sensitivity to alignment mismatches. Such behavior highlights the limitations of these metrics in providing fair and unbiased evaluations across diverse model architectures.

**VQA Score and TIFA Score are relative reliable metrics.** Among the evaluated metrics, *VQA Score* and *TIFA Score* stand out by assessing model performance on VQA tasks, rather than relying solely on subjective human preferences. This approach enhances the interpretability of the evaluation process. Additionally, we observed that the results from *VQA Score* and *TIFA Score* show a stronger correlation with other established benchmarks. Based on these advantages, we recommend prioritizing these two metrics for evaluation. However, it is important to note that their effectiveness is constrained by the limitations of the VQA models utilized in the evaluation.

### A.3.3 Fairness analysis

We evaluate fairness by examining the model’s performance across different genders and races. Specifically, we calculate the average performance for each node and its associated child nodes within the taxonomy tree constructed for objects. For example, the node “females” includes child nodes such as “waitresses,” and their combined performance is considered in the analysis.

**Gender.** In gender, we observe a notable performance gap between females and males, as could be seen from Figure 11. Models are better at generating male concepts.

**Race.** There are also performance gaps in different races. From Figure 12, we found that “white (person)” and “black (person)” perform better than “asian (person)”, “Indian (amerindian)”, and “Latin American”.

### A.3.4 Correlation of GENERATE ANY SCENE with other Text-to-Vision generation benchmarks

The GENERATE ANY SCENE benchmark uniquely relies entirely on synthetic captions to evaluate models. To assess the transferability of these synthetic captions, we analyzed the consistency in model rankings across different benchmarks [79, 38, 92]. Specifically, we identified the overlap of models evaluated by two benchmarks and computed the Spearman correlation coefficient between their rankings.

As shown in the figure 13, GENERATE ANY SCENE demonstrates a strong correlation with other benchmarks, such as Conceptmix [79] and GenAI Bench [38], indicating the robustness and reliability

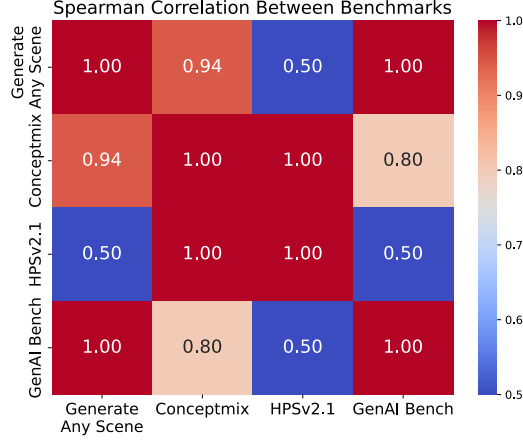
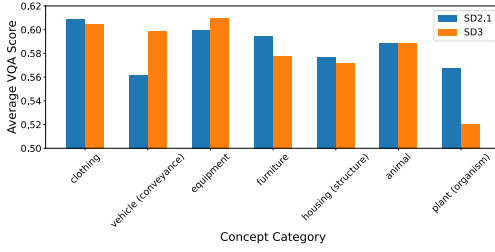
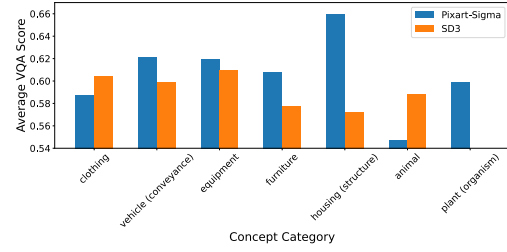


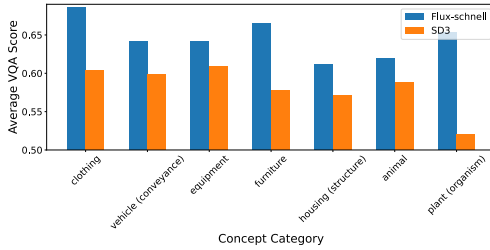
Figure 13: Correlation of GENERATE ANY SCENE with other popular *Text-to-Vision* generation benchmarks.



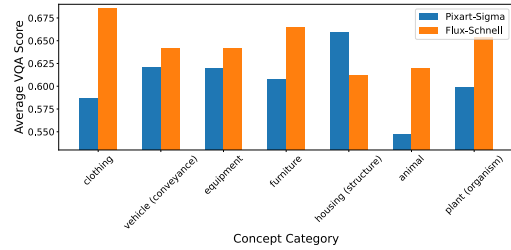
(a) *SDv2.1* vs. *SD3 Medium* on average *VQA Score* in fine-grained categories.



(b) *PixArt- $\Sigma$*  vs. *SD3 Medium* on average *VQA Score* in fine-grained categories.



(c) *FLUX.1-schnell* vs. *SD3 Medium* on average *VQA Score* in fine-grained categories.



(d) *PixArt- $\Sigma$*  vs. *FLUX.1-schnell* on average *VQA Score* in fine-grained categories.

Figure 14: Pairwise comparison on average *VQA Score* in fine-grained categories.

777 of GENERATE ANY SCENE’s synthetic caption-based evaluations. This suggests that the synthetic  
 778 captions generated by GENERATE ANY SCENE can effectively reflect model performance trends,  
 779 aligning closely with those observed in benchmarks using real-world captions or alternative evaluation  
 780 methods.

### 781 A.3.5 Case study: Pairwise fine-grained model comparison

782 Evaluating models using a single numerical average score can be limiting, as different training data  
 783 often lead models to excel in generating different types of concepts. By leveraging the taxonomy we  
 784 developed for GENERATE ANY SCENE, we can systematically organize these concepts and evaluate  
 785 each model’s performance on specific concepts over the taxonomy. This approach enables a more  
 786 detailed comparison of how well models perform on individual concepts rather than relying solely on  
 787 an overall average score. Our analysis revealed that, while the models may achieve similar average



788 performance, their strengths and weaknesses vary significantly across different concepts. Here we  
789 present a pairwise comparison of models across different metrics.

## B Details of Taxonomy of Visual Concepts

To construct a scene graph, we utilize three primary types of metadata: objects, attributes, and relations, which represent the structure of a visual scene. Additionally, scene attributes—which include factors like image style, perspective, and video time span—capture broader aspects of the visual content. Together, the scene graph and scene attributes form a comprehensive representation of the scene.

Our metadata is further organized using a well-defined taxonomy, enhancing the ability to generate controllable captions. This hierarchical taxonomy not only facilitates the creation of diverse scene graphs, but also enables fine-grained and systematic model evaluation.

**Objects.** To enhance the comprehensiveness and taxonomy of object data, we leverage noun synsets and the structure of WordNet [32]. In WordNet, a *physical object* is defined as “a tangible and visible entity; an entity that can cast a shadow.” Following this definition, we designate the *physical object* as the root node, constructing a hierarchical tree with all 28,787 hyponyms under this category as the set of objects in our model.

Following WordNet’s hypernym-hyponym relationships, we establish a tree structure, linking each object to its primary parent node based on its first-listed hypernym. For objects with multiple hypernyms, we retain only the primary parent to simplify the hierarchy. Furthermore, to reduce ambiguity, if multiple senses of a term share the same parent, we exclude that term itself and reassign its children to the original parent node. This approach yields a well-defined and disambiguated taxonomy.

**Attributes.** The attributes of a scene graph represent properties or characteristics associated with each object. We classify these attributes into *nine* primary categories. For *color*, we aggregate 677 unique entries sourced from Wikipedia [33]. The *material* category comprises 76 types, referenced from several public datasets [93, 94, 95]. The *texture* category includes 42 kinds from the Describable Textures Dataset [96], while the *architectural style* encompasses 25 distinct styles [97]. Additionally, we collect 85 *states*, 41 *shapes*, and 24 *sizes*. For *human descriptors*, we compile 59 terms across subcategories, including body type and height. Finally, we collect 465 common *adjectives* covering general characteristics of objects to enhance the descriptive richness of our scene graphs.

**Relationships.** We leverage the Robin dataset [34] as the foundation for relationship metadata, encompassing six key categories: spatial, functional, interactional, social, emotional, and symbolic. With 10,492 relationships, the dataset provides a comprehensive and systematic repository that supports modeling diverse and complex object interactions. Its extensive coverage captures both tangible and abstract connections, forming a robust framework for accurate scene graph representation.

**Scene Attributes.** In *Text-to-Vision generation* tasks, people mainly focus on creating realistic images and art from a text description [98, 2, 3]. For artistic styles, we define scene attributes using 76 renowned *artists*, 41 *genres*, and 126 *painting styles* from WikiArt [99], along with 29 common *painting techniques*. For realistic imagery, we construct camera settings attributes across 6 categories: camera models, focal lengths, perspectives, apertures, depths of field, and shot scales. The camera models are sourced from the 1000 Cameras Dataset [100], while the remaining categories are constructed based on photography knowledge and common captions in *Text-to-Vision generation* tasks [1, 101]. To control scene settings, we categorize location, weather and lighting attributes, using 430 diverse locations from Places365 [35], alongside 76 *weathers* and 57 *lighting conditions*. For video generation, we introduce attributes that describe dynamic elements. These include 12 types of camera rig, 30 distinct camera movements, 15 video editing styles, and 27 temporal spans. The comprehensive scene attributes that we construct allow for the detailed and programmatic *Text-to-Vision generation*.

## 836 C Details of self-improving models with synthetic captions (Section 3)

### 837 C.1 Experiment details

#### 838 C.1.1 Captions Preparation

839 To evaluate the effectiveness of our iterative self-improving *Text-to-Vision generation* model, we  
840 generated three distinct sets of 10K captions using GENERATE ANY SCENE, covering a sample  
841 complexity range from 3 to 12. These captions were programmatically created to reflect a spectrum  
842 of structured scene graph compositions, designed to challenge and enrich the model’s learning  
843 capabilities.

844 For comparative analysis, we leveraged the Conceptual Captions (CC3M) [102] dataset, a large-scale  
845 benchmark containing approximately 3.3 million image-caption pairs sourced from web alt-text  
846 descriptions. CC3M is renowned for its diverse visual content and natural language expressions,  
847 encompassing a wide range of styles, contexts, and semantic nuances.

848 To ensure fair comparison, we randomly sampled three subsets of 10K captions from the CC3M  
849 dataset, matching the GENERATE ANY SCENE-generated caption sets in size. This approach stan-  
850 dardizes data volume while enabling direct performance evaluation. The diversity and semantic  
851 richness of the CC3M captions serve as a robust benchmark to assess whether GENERATE ANY  
852 SCENE-generated captions can match or exceed the descriptive quality of real-world data across  
853 varied visual contexts.

#### 854 C.1.2 Dataset Construction and Selection Strategies

855 For the captions generated by GENERATE ANY SCENE, we employed a top-scoring selection strategy  
856 to construct the fine-tuning training dataset, using a random selection strategy as a baseline for  
857 comparison. Specifically, for each caption, the model generated eight images. Under the top-scoring  
858 strategy, we evaluated the generated images using the VQA score and selected the highest-scoring  
859 image as the best representation of the caption. This process yielded 10K top-ranked images per  
860 iteration, from which the top 25% (approximately 2.5k images) with the highest VQA scores were  
861 selected to form the fine-tuning dataset.

862 In the random selection strategy, one image was randomly chosen from the eight generated per  
863 caption, and 25% of these 10K randomly selected images were sampled to create the fine-tuning  
864 dataset, maintaining parity in data size.

865 For the CC3M dataset, each caption was uniquely paired with a real image. From the 10K real  
866 image-caption pairs sampled from CC3M, the top 25% with the highest VQA scores were selected as  
867 the fine-tuning training dataset. This ensured consistency in data size and selection criteria across all  
868 methods, facilitating a rigorous and equitable comparison of fine-tuning strategies.

#### 869 C.1.3 Fine-tuning details

870 We fine-tuned the *SDv1.5* using the LoRA technique. The training was conducted with a resolution  
871 of  $512 \times 512$  for input images and a batch size of 8. Gradients were accumulated over two steps.  
872 The optimization process utilized the AdamW optimizer with  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ , an  $\epsilon$  value of  
873  $1 \times 10^{-8}$ , and a weight decay of  $10^{-2}$ . The learning rate was set to  $1 \times 10^{-4}$  and followed a cosine  
874 scheduler for smooth decay during training. To ensure stability, a gradient clipping threshold of 1.0  
875 was applied. The fine-tuning process was executed for one epoch, with a maximum of 2500 training  
876 steps. For the LoRA-specific configurations, we set the rank of the low-rank adaptation layers and  
877 the scaling factor  $\alpha$  to be 128.

878 After completing fine-tuning for each epoch, we set the LoRA weight to 0.75 and integrate it into  
879 *SDv1.5* to guide image generation and selection for the next subset. For the CC3M dataset, images  
880 from the subsequent subset are directly selected.

881 In the following epoch, the fine-tuned LoRA parameters from the previous epoch are loaded and  
882 used to resume training on the current subset, ensuring continuity and leveraging the incremental  
883 improvements from prior iterations.

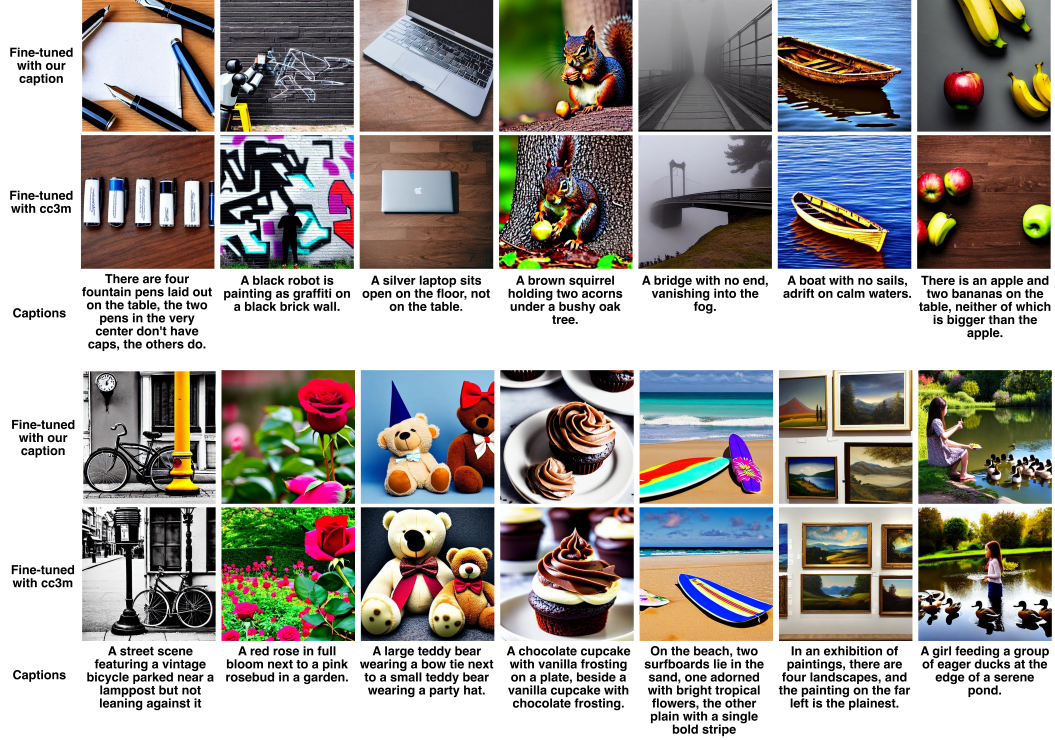


Figure 15: Visualization of Different Caption Fine-Tuning.

In Figure 15, we present results using our captions and the CC3M captions. The model fine-tuned with captions generated by GENERATE ANY SCENE demonstrates superior performance in terms of text semantic relevance and the generation of complex compositional scenes.

## C.2 More results of fine-tuning models

Aside from our own test set and GenAI benchmark, we also evaluated our fine-tuned *Text-to-Image* generation models on the Tifa Bench (Figure 16), where we observed the same trend: models fine-tuned with our captions consistently outperformed the original *SDv1.5* and CC3M fine-tuned models.

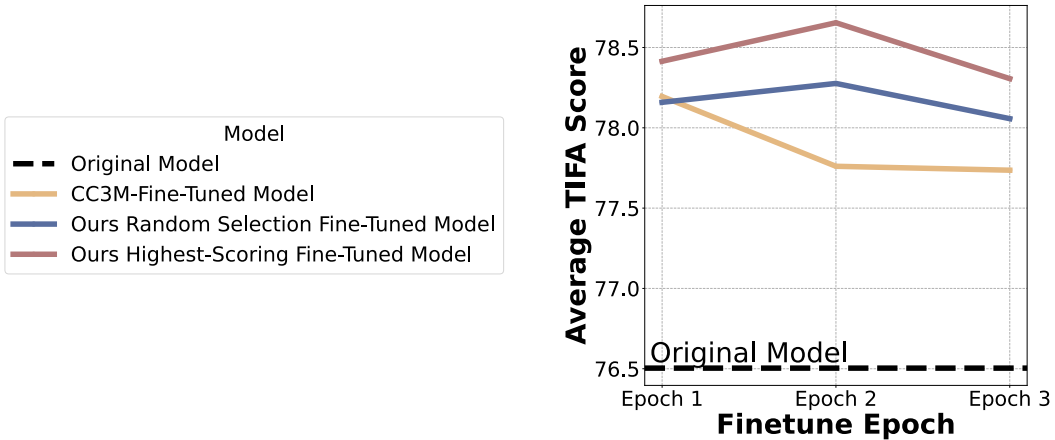


Figure 16: Results for Application 1: Self-Improving Models. Average TIFA score of *SDv1.5* fine-tuned with different data over TIFA Bench.

## D Details of distilling targeted capabilities (Section 4)

### D.1 Collecting hard concepts

We selected 81 challenging object concepts where *SDv1.5* and *DaLL-E 3* exhibit the largest gap in *VQA Score*. To determine the score for each concept, we calculated the average VQA score of the captions containing that specific concept. The full list of hard concepts is shown below:

1. cloverleaf
2. aerie (habitation)
3. admixture
4. webbing (web)
5. platter
6. voussoir
7. hearthstone
8. puttee
9. biretta
10. yarmulke
11. surplice
12. overcoat
13. needlepoint
14. headshot
15. photomicrograph
16. lavalier
17. crepe
18. tureen
19. bale
20. jetliner
21. square-rigger
22. supertanker
23. pocketcomb
24. filament (wire)
25. inverter
26. denture
27. lidar
28. volumeter
29. colonoscope
30. synchrocyclotron
31. miller (shaper)
32. alternator
33. dicer
34. trundle
35. paddle (blade)
36. harmonica
37. piccolo
38. handrest

|     |                                    |
|-----|------------------------------------|
| 935 | 39. rundle                         |
| 936 | 40. blowtorch                      |
| 937 | 41. volleyball                     |
| 938 | 42. tile (man)                     |
| 939 | 43. shuttlecock                    |
| 940 | 44. jigsaw                         |
| 941 | 45. roaster (pan)                  |
| 942 | 46. maze                           |
| 943 | 47. belt (ammunition)              |
| 944 | 48. gaddi                          |
| 945 | 49. drawer (container)             |
| 946 | 50. tenter                         |
| 947 | 51. pinnacle (steeple)             |
| 948 | 52. pegboard                       |
| 949 | 53. afterdeck                      |
| 950 | 54. scaffold                       |
| 951 | 55. catheter                       |
| 952 | 56. broomcorn                      |
| 953 | 57. spearmint                      |
| 954 | 58. okra (herb)                    |
| 955 | 59. goatsfoot                      |
| 956 | 60. peperomia                      |
| 957 | 61. ammobium                       |
| 958 | 62. gazania                        |
| 959 | 63. echinocactus                   |
| 960 | 64. birthwort                      |
| 961 | 65. love-in-a-mist (passionflower) |
| 962 | 66. ragwort                        |
| 963 | 67. spicebush (allspice)           |
| 964 | 68. leadplant                      |
| 965 | 69. barberry                       |
| 966 | 70. hamelia                        |
| 967 | 71. jimsonweed                     |
| 968 | 72. undershrub                     |
| 969 | 73. dogwood                        |
| 970 | 74. butternut (walnut)             |
| 971 | 75. bayberry (tree)                |
| 972 | 76. lodestar                       |
| 973 | 77. tapa (bark)                    |
| 974 | 78. epicalyx                       |
| 975 | 79. blackberry (berry)             |
| 976 | 80. stub                           |
| 977 | 81. shag (tangle)                  |



## D.2 Experiment details

We conducted targeted fine-tuning experiments on *SDv1.5* to evaluate GENERATE ANY SCENE’s effectiveness in distilling model compositionality and learning hard concepts. For each task, we selected a dataset of 778 GENERATE ANY SCENE captions paired with images generated by *DaLL-E 3*. For compositionality, we selected multi-object captions from the existing dataset of 10K GENERATE ANY SCENE captions and paired them with the corresponding images generated by *DaLL-E 3*. To address hard concept learning, we first used *SDv1.5* to generate images based on the 10K GENERATE ANY SCENE captions and identified the hard concepts with the lowest VQA scores. These concepts were then used to create a subset of objects, which we recombined into our scene-graph based captions with complexity levels ranging from 3 to 9. Finally, we used *DaLL-E 3* to generate corresponding images for these newly composed captions.

The fine-tuning configurations were consistent with those used in the self-improving setup (Appendix C.1.3). To accommodate the reduced dataset size, the maximum training steps were set to 1000.

As a baseline, we randomly selected 778 images from 10K GENERATE ANY SCENE-generated images, using captions produced by GENERATE ANY SCENE. This ensured a controlled comparison between the targeted and random fine-tuning strategies.

## E Details of reinforcement learning with a synthetic reward function (Section 5)

### E.1 Training data preparation

We adopt SimpleAR-0.5B-SFT [26] as our base model. Given that SimpleAR-0.5B-SFT is pretrained on high-quality real image datasets such as LAION [11] and CC3M [12], we aim to mitigate potential distributional shift between the original training data and the reinforcement learning phase. To this end, we perform metadata pre-selection for GENERATE ANY SCENE by analyzing the frequency of each object category appearing in the LAION dataset. Leveraging the controllable compositional capabilities of GENERATE ANY SCENE, we filter object categories by selecting the top 10% most frequent entries and constrain scene complexity to 3–6 objects per scene. Based on these conditions, we synthesize a set of 10K captions, ensuring semantic alignment with the base model’s pretraining distribution while maintaining structural and content diversity.

### E.2 Experiment details

The detailed training configuration is provided in Table 7. We utilize  $8 \times$  NVIDIA H100 GPUs (80GB HBM3), with one GPU allocated for online generation using vLLM. The total training time is approximately 14 hours.

Table 7: Scene-graph based GRPO Fine-tuning Configuration for SimpleAR

| Component             | Details                              |
|-----------------------|--------------------------------------|
| Model Name            | SimpleAR-0.5B-SFT                    |
| Model Size            | $\sim 0.5$ B parameters              |
| Training Policy       | GRPO                                 |
| Inference Engine      | vLLM (GPU utilization = 0.7)         |
| Completion Length     | 4096 tokens                          |
| Training Epochs       | 1                                    |
| Batch Size per Device | 4                                    |
| Learning Rate         | $1 \times 10^{-5}$                   |
| Scheduler             | Cosine Annealing (min lr rate = 0.1) |
| Warm-up Ratio         | 0.1                                  |
| Gradient Accumulation | 1                                    |

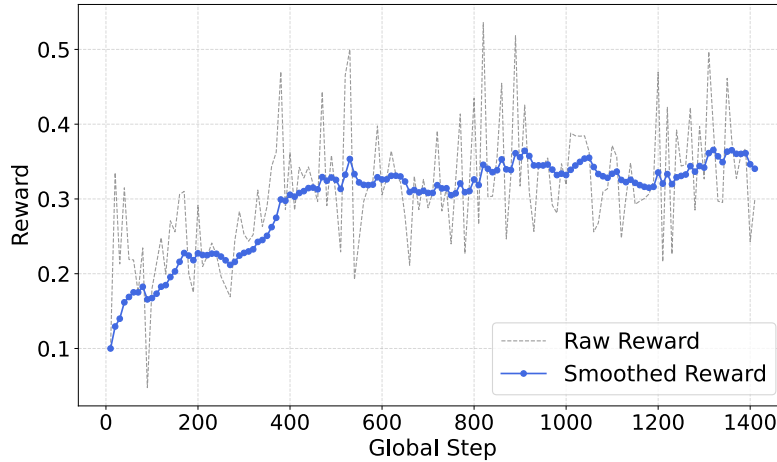


Figure 17: Reward progression during scene-graph based GRPO training.

Figure 17 illustrates the reward progression during training. A noticeable improvement in reward is observed following the application of a learning rate of  $1e-5$  combined with a warm-up strategy.

1013 Overall, the reward increases by approximately 0.2, indicating effective learning under the adjusted  
1014 training configuration.

1015 In Table 2, we observe that the reproduced results of baseline models on DPG-Bench and GenEval  
1016 Bench are slightly lower than those reported in the original paper. Considering the inherent stochas-  
1017 ticity in generative model outputs, we cite the original results for comparison. For GenAI-Bench, all  
1018 reported results are based on our own experimental evaluations.

## F Details of improving generated-content detection (Section 6)

### F.1 Experiment details

In this section, our goal is to validate that the more diverse captions generated by GENERATE ANY SCENE can complement existing datasets, which are predominantly composed of real-world images paired with captions. By doing so, we aim to train AI-generated content detectors to achieve greater robustness.

**Dataset preparation** We conducted comparative experiments between captions generated by GENERATE ANY SCENE and entries from the  $D^3$  dataset. From the  $D^3$  dataset, we randomly sampled 10K entries, each including a caption, a link to a real image, and an image generated by SD v1.4. Due to some broken links, we successfully downloaded 8.5K real images and retained 10K SD v1.4-generated images. We also used SD v1.4 to generate images based on 10K GENERATE ANY SCENE captions.

We varied the training data sizes based on the sampled dataset. Specifically, we sampled  $N$  real images from the 10K  $D^3$  real images. For synthetic data, we compared  $N$  samples exclusively from  $D^3$  with a mixed set of  $N/2$  samples from 10K GENERATE ANY SCENE images and  $N/2$  sampled from  $D^3$ , ensuring a total of  $N$  synthetic samples. Combined, this resulted in  $2N$  training images. We tested  $2N$  across various sizes, ranging from 2K to 10K.

**Detector architecture and training** We employed ViT-T [47] and ResNet-18 [103] as backbones for the detection models. Their pretrained parameters on ImageNet-21K were frozen, and the final classification head was replaced with a linear layer using a sigmoid activation function to predict the probability of an image being AI-generated. During training, We used Binary Cross-Entropy (BCE) as the loss function, and the AdamW optimizer was applied with a learning rate of  $2e^{-3}$ . Training was conducted with a batch size of 256 for up to 50 epochs, with early stopping triggered after six epochs of no improvement in validation performance.

**Testing** To evaluate the performance of models trained with varying dataset sizes and synthetic data combinations, we tested them on both GenImage and GENERATE ANY SCENE datasets to assess their in-domain and out-of-domain performance under different settings.

For GenImage, we used validation data from four models: SD v1.4, SD v1.5, MidJourney, and VQDM. Each validation set contained 8K real images and 8k generated images. For GENERATE ANY SCENE, we sampled 10K real images from CC3M and paired them with 10K generated images from each of the following models: *SDv2.1*, *PixArt- $\alpha$* , *SD3 Medium*, and *Playground v2.5*. This created distinct test sets for evaluating model performance across different synthetic data sources.

Table 8: F1-Score Comparison of ResNet-18 and ViT-T Detectors Trained with  $D^3$  and  $D^3$ + GENERATE ANY SCENE Across In-Domain Settings

| Detector  | Data Scale (2N) | SDv1.4<br>(In-domain, same model) |               | SDv2.1       |        | Pixart- $\alpha$ |        | SDv3-medium  |        | Playground v2.5 |        | Average<br>(In-domain, cross model) |        |
|-----------|-----------------|-----------------------------------|---------------|--------------|--------|------------------|--------|--------------|--------|-----------------|--------|-------------------------------------|--------|
|           |                 | $D^3$ + Ours                      | $D^3$         | $D^3$ + Ours | $D^3$  | $D^3$ + Ours     | $D^3$  | $D^3$ + Ours | $D^3$  | $D^3$ + Ours    | $D^3$  | $D^3$ + Ours                        | $D^3$  |
| Resnet-18 | 2K              | 0.6561                            | <b>0.6663</b> | 0.7682       | 0.6750 | 0.7379           | 0.606  | 0.7509       | 0.6724 | 0.7380          | 0.5939 | <b>0.7488</b>                       | 0.6368 |
|           | 4K              | 0.6751                            | <b>0.6812</b> | 0.7624       | 0.6853 | 0.7328           | 0.6494 | 0.7576       | 0.7028 | 0.7208          | 0.6163 | <b>0.7434</b>                       | 0.6635 |
|           | 6K              | 0.6780                            | <b>0.6995</b> | 0.7886       | 0.6870 | 0.7493           | 0.6586 | 0.7768       | 0.7285 | 0.7349          | 0.6335 | <b>0.7624</b>                       | 0.6769 |
|           | 8K              | 0.6828                            | <b>0.6964</b> | 0.7710       | 0.6741 | 0.7454           | 0.6418 | 0.7785       | 0.7186 | 0.7215          | 0.6033 | <b>0.7541</b>                       | 0.6595 |
|           | 10K             | 0.6830                            | <b>0.6957</b> | 0.7807       | 0.6897 | 0.7483           | 0.6682 | 0.7781       | 0.7326 | 0.7300          | 0.6229 | <b>0.7593</b>                       | 0.6784 |
| ViT-T     | 2K              | <b>0.6759</b>                     | 0.6672        | 0.7550       | 0.6827 | 0.7585           | 0.6758 | 0.7473       | 0.6941 | 0.7327          | 0.6106 | <b>0.7484</b>                       | 0.6658 |
|           | 4K              | <b>0.6878</b>                     | 0.6871        | 0.7576       | 0.7000 | 0.7605           | 0.7071 | 0.7549       | 0.7217 | 0.7221          | 0.6144 | <b>0.7488</b>                       | 0.6858 |
|           | 6K              | <b>0.6898</b>                     | 0.6891        | 0.7663       | 0.6962 | 0.7666           | 0.7164 | 0.7629       | 0.7238 | 0.7303          | 0.6134 | <b>0.7565</b>                       | 0.6875 |
|           | 8K              | 0.6962                            | <b>0.6974</b> | 0.7655       | 0.6894 | 0.7712           | 0.7253 | 0.7653       | 0.7253 | 0.7381          | 0.6344 | <b>0.7600</b>                       | 0.6936 |
|           | 10K             | <b>0.6986</b>                     | 0.6984        | 0.7828       | 0.6960 | 0.7777           | 0.7275 | 0.7786       | 0.7334 | 0.7330          | 0.6293 | <b>0.7680</b>                       | 0.6966 |

### F.2 Results

Table 9 and Table 8 evaluate the performance of ResNet-18 and ViT-T detection backbones trained on datasets of varying sizes and compositions across in-domain (same model and cross-model) and out-of-domain settings. While models trained with  $D^3$  and GENERATE ANY SCENE occasionally underperform compared to those trained solely on  $D^3$  in the in-domain same-model setting, they exhibit significant advantages in both in-domain cross-model and out-of-domain evaluations. These results demonstrate that incorporating our data (GENERATE ANY SCENE) into the training process

enhances the detector’s robustness. By supplementing existing datasets with GENERATE ANY SCENE under the same training configurations and dataset sizes, detectors achieve stronger cross-model and cross-dataset capabilities, highlighting improved generalizability to diverse generative models and datasets.

Table 9: F1-Score Comparison of ResNet-18 and ViT-T Detectors Trained with  $D^3$  and  $D^3$  + GENERATE ANY SCENE Across Out-of-Domain Settings

| Detector  | Data Scale<br>(2N) | SDv1.5       |        | VQDM         |        | Midjourney   |        | Average<br>(Out-of-domain) |        |
|-----------|--------------------|--------------|--------|--------------|--------|--------------|--------|----------------------------|--------|
|           |                    | $D^3$ + Ours | $D^3$  | $D^3$ + Ours | $D^3$  | $D^3$ + Ours | $D^3$  | $D^3$ + Ours               | $D^3$  |
| Resnet-18 | 2K                 | 0.6515       | 0.6591 | 0.5629       | 0.5285 | 0.5803       | 0.5647 | <b>0.5982</b>              | 0.5841 |
|           | 4K                 | 0.6709       | 0.6817 | 0.5693       | 0.5428 | 0.6016       | 0.5941 | <b>0.6139</b>              | 0.6062 |
|           | 6K                 | 0.6750       | 0.6963 | 0.5724       | 0.5327 | 0.6084       | 0.6072 | <b>0.6186</b>              | 0.6121 |
|           | 8K                 | 0.6792       | 0.6965 | 0.5716       | 0.5282 | 0.6097       | 0.5873 | <b>0.6202</b>              | 0.6040 |
|           | 10K                | 0.6814       | 0.6955 | 0.5812       | 0.5454 | 0.6109       | 0.6040 | <b>0.6245</b>              | 0.6150 |
| ViT-T     | 2K                 | 0.6755       | 0.6685 | 0.5443       | 0.4966 | 0.6207       | 0.6066 | <b>0.6135</b>              | 0.5906 |
|           | 4K                 | 0.6845       | 0.6865 | 0.5591       | 0.4971 | 0.6416       | 0.6149 | <b>0.6284</b>              | 0.5995 |
|           | 6K                 | 0.6900       | 0.6890 | 0.5580       | 0.4948 | 0.6455       | 0.6259 | <b>0.6313</b>              | 0.6032 |
|           | 8K                 | 0.6940       | 0.6969 | 0.5553       | 0.4962 | 0.6495       | 0.6387 | <b>0.6329</b>              | 0.6106 |
|           | 10K                | 0.6961       | 0.6988 | 0.5499       | 0.4975 | 0.6447       | 0.6358 | <b>0.6302</b>              | 0.6107 |

## 1062 G Limitation

1063 **Programmatically generated prompts can be unrealistic and biased.** Programmatically gener-  
1064 ated prompts can be unrealistic and biased. Although our system is capable of producing a wide range  
1065 of rare compositional scenes and corresponding prompts, some of these outputs may violate rules or  
1066 conventions, going beyond what is even considered imaginable or plausible. We also implement a  
1067 pipeline to filter the commonsense of the generated prompts using the *Vera score* (a large language  
1068 model-based commonsense metric) and *Perplexity*, but we make this pipeline **optional**.

1069 **Linguistic diversity of programmatic prompts is limited.** While GENERATE ANY SCENE excels  
1070 at generating diverse and compositional scene graphs and prompts, its ability to produce varied  
1071 language expressions is somewhat constrained. The programmatic approach to generating content  
1072 ensures diversity in terms of the elements of the scene, but it is limited when it comes to linguistic  
1073 diversity and the richness of expression. To address this, we introduce a pipeline that leverages large  
1074 language models (LLMs) to paraphrase prompts, enhancing linguistic variety. However, this addition  
1075 introduces new challenges. LLMs are prone to biases and hallucinations, which can affect the quality  
1076 and reliability of the output. Furthermore, the use of LLMs risks distorting the integrity of the original  
1077 scene graph structure, compromising the coherence and accuracy of the generated content. So we  
1078 make this LLM paraphrase pipeline **optional** for our paper.

1079 **Toward curriculum-aware GRPO training.** Our proposed GENERATE ANY SCENE framework  
1080 plays a central role in GRPO training by providing structured scene graphs that serve as the foun-  
1081 dation for a semantically grounded and controllable reward function. This design enables effective  
1082 optimization by aligning generation objectives with fine-grained visual semantics. Beyond this, we  
1083 also observe that GENERATE ANY SCENE also offers broader potential: the scene graphs it produces  
1084 vary in complexity, such as in the number of objects, attributes, relationships and graph degree.  
1085 These variations naturally correspond to different levels of generation difficulty and reward variance.  
1086 This property suggests an opportunity for curriculum-based training, where the model could be  
1087 progressively exposed to increasingly complex scene graphs. Such a strategy may improve training  
1088 stability and efficiency, especially in the early stages of learning. We identify this as a promising  
1089 direction for future work, further leveraging the controllability of GENERATE ANY SCENE to guide  
1090 structured policy learning.

## Appendix References

- [1] Tim Brooks, Bill Peebles, Connor Holmes, Will DePue, Yufei Guo, Li Jing, David Schnurr, Joe Taylor, Troy Luhman, Eric Luhman, et al. Video generation models as world simulators. 2024. URL <https://openai.com/research/video-generation-models-as-world-simulators>, 3, 2024.
- [2] 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.
- [3] James Betker, Gabriel Goh, Li Jing, Tim Brooks, Jianfeng Wang, Linjie Li, Long Ouyang, Juntang Zhuang, Joyce Lee, Yufei Guo, et al. Improving image generation with better captions. *Computer Science*. <https://cdn.openai.com/papers/dall-e-3.pdf>, 2(3):8, 2023.
- [4] Zhengyi Wang, Cheng Lu, Yikai Wang, Fan Bao, Chongxuan Li, Hang Su, and Jun Zhu. Prolificdreamer: High-fidelity and diverse text-to-3d generation with variational score distillation. *Advances in Neural Information Processing Systems*, 36, 2024.
- [5] Junsong Chen, Jincheng Yu, Chongjian Ge, Lewei Yao, Enze Xie, Yue Wu, Zhongdao Wang, James T. Kwok, Ping Luo, Huchuan Lu, and Zhenguo Li. Pixart- $\alpha$ : Fast training of diffusion transformer for photorealistic text-to-image synthesis. *ArXiv*, abs/2310.00426, 2023.
- [6] Bohao Peng, Jian Wang, Yuechen Zhang, Wenbo Li, Ming-Chang Yang, and Jiaya Jia. Controlnext: Powerful and efficient control for image and video generation. *arXiv preprint arXiv:2408.06070*, 2024.
- [7] Kaiyi Huang, Kaiyue Sun, Enze Xie, Zhenguo Li, and Xihui Liu. T2i-compbench: A comprehensive benchmark for open-world compositional text-to-image generation. *ArXiv*, abs/2307.06350, 2023.
- [8] Kaiyue Sun, Kaiyi Huang, Xian Liu, Yue Wu, Zihan Xu, Zhenguo Li, and Xihui Liu. T2v-compbench: A comprehensive benchmark for compositional text-to-video generation. *ArXiv*, abs/2407.14505, 2024.
- [9] Dhruba Ghosh, Hannaneh Hajishirzi, and Ludwig Schmidt. Geneval: An object-focused framework for evaluating text-to-image alignment. *Advances in Neural Information Processing Systems*, 36:52132–52152, 2023.
- [10] Xiwei Hu, Rui Wang, Yixiao Fang, Bin Fu, Pei Cheng, and Gang Yu. Ella: Equip diffusion models with llm for enhanced semantic alignment. *arXiv preprint arXiv:2403.05135*, 2024.
- [11] Christoph Schuhmann, Romain Beaumont, Richard Vencu, Cade Gordon, Ross Wightman, Mehdi Cherti, Theo Coombes, Aarush Katta, Clayton Mullis, Mitchell Wortsman, et al. Laion-5b: An open large-scale dataset for training next generation image-text models. *Advances in neural information processing systems*, 35:25278–25294, 2022.
- [12] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 2556–2565, 2018.
- [13] Zejian Li, Chenye Meng, Yize Li, Ling Yang, Shengyuan Zhang, Jiarui Ma, Jiayi Li, Guang Yang, Changyuan Yang, Zhiyuan Yang, et al. Laion-sg: An enhanced large-scale dataset for training complex image-text models with structural annotations. *arXiv preprint arXiv:2412.08580*, 2024.
- [14] Ranjay Krishna, Yuke Zhu, Oliver Groth, Justin Johnson, Kenji Hata, Joshua Kravitz, Stephanie Chen, Yannis Kalantidis, Li-Jia Li, David A Shamma, et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision*, 123:32–73, 2017.



- 1138 [15] Justin Johnson, Ranjay Krishna, Michael Stark, Li-Jia Li, David Shamma, Michael Bernstein,  
1139 and Li Fei-Fei. Image retrieval using scene graphs. In *Proceedings of the IEEE conference on*  
1140 *computer vision and pattern recognition*, pages 3668–3678, 2015.
- 1141 [16] Julian Ost, Fahim Mannan, Nils Thuerey, Julian Knodt, and Felix Heide. Neural scene graphs  
1142 for dynamic scenes. In *Proceedings of the IEEE/CVF Conference on Computer Vision and*  
1143 *Pattern Recognition*, pages 2856–2865, 2021.
- 1144 [17] Justin Johnson, Agrim Gupta, and Li Fei-Fei. Image generation from scene graphs. In  
1145 *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1219–  
1146 1228, 2018.
- 1147 [18] Jingwei Ji, Ranjay Krishna, Li Fei-Fei, and Juan Carlos Niebles. Action genome: Actions as  
1148 compositions of spatio-temporal scene graphs. In *Proceedings of the IEEE/CVF Conference*  
1149 *on Computer Vision and Pattern Recognition*, pages 10236–10247, 2020.
- 1150 [19] Irving Biederman. Recognition-by-components: a theory of human image understanding.  
1151 *Psychological review*, 94(2):115, 1987.
- 1152 [20] Cewu Lu, Ranjay Krishna, Michael Bernstein, and Li Fei-Fei. Visual relationship detection  
1153 with language priors. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam,*  
1154 *The Netherlands, October 11–14, 2016, Proceedings, Part I 14*, pages 852–869. Springer,  
1155 2016.
- 1156 [21] Jieyu Zhang, Weikai Huang, Zixian Ma, Oscar Michel, Dong He, Tanmay Gupta, Wei-Chiu  
1157 Ma, Ali Farhadi, Aniruddha Kembhavi, and Ranjay Krishna. Task me anything. In *Advances*  
1158 *in neural information processing systems*, 2024.
- 1159 [22] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer.  
1160 High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF*  
1161 *Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10684–10695, June  
1162 2022.
- 1163 [23] Yushi Hu, Benlin Liu, Jungo Kasai, Yizhong Wang, Mari Ostendorf, Ranjay Krishna, and  
1164 Noah A Smith. Tifa: Accurate and interpretable text-to-image faithfulness evaluation with  
1165 question answering, 2023.
- 1166 [24] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin,  
1167 Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton,  
1168 Fraser Kelton, Luke E. Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Francis  
1169 Christiano, Jan Leike, and Ryan J. Lowe. Training language models to follow instructions  
1170 with human feedback. *ArXiv*, abs/2203.02155, 2022.
- 1171 [25] Zhihong Shao, Peiyi Wang, Qihao Zhu, Runxin Xu, Junxiao Song, Xiao Bi, Haowei Zhang,  
1172 Mingchuan Zhang, Y. K. Li, Y. Wu, and Daya Guo. Deepseekmath: Pushing the limits of  
1173 mathematical reasoning in open language models, 2024.
- 1174 [26] Junke Wang, Zhi Tian, Xun Wang, Xinyu Zhang, Weilin Huang, Zuxuan Wu, and Yu-Gang  
1175 Jiang. Simplear: Pushing the frontier of autoregressive visual generation through pretraining,  
1176 sft, and rl. *arXiv preprint arXiv:2504.11455*, 2025.
- 1177 [27] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini  
1178 Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and  
1179 Ilya Sutskever. Learning transferable visual models from natural language supervision, 2021.
- 1180 [28] Xiwei Hu, Rui Wang, Yixiao Fang, Bin Fu, Pei Cheng, and Gang Yu. Ella: Equip diffusion  
1181 models with llm for enhanced semantic alignment, 2024.
- 1182 [29] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai,  
1183 Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly,  
1184 Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image  
1185 recognition at scale, 2021.

- [30] Drew A Hudson and Christopher D Manning. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 6700–6709, 2019.
- [31] Jaemin Cho, Yushi Hu, Roopal Garg, Peter Anderson, Ranjay Krishna, Jason Baldridge, Mohit Bansal, Jordi Pont-Tuset, and Su Wang. Davidsonian scene graph: Improving reliability in fine-grained evaluation for text-to-image generation. *ArXiv*, abs/2310.18235, 2023.
- [32] George A Miller. Wordnet: a lexical database for english. *Communications of the ACM*, 38(11):39–41, 1995.
- [33] Wikipedia Contributors. Lists of colors. [https://en.wikipedia.org/wiki/Lists\\_of\\_colors](https://en.wikipedia.org/wiki/Lists_of_colors), 2024. Accessed: 2024-11-09.
- [34] Jae Sung Park, Zixian Ma, Linjie Li, Chenhao Zheng, Cheng-Yu Hsieh, Ximing Lu, Khyathi Chandu, Quan Kong, Norimasa Kobori, Ali Farhadi, Yejin Choi, and Ranjay Krishna. Synthetic visual genome. In *CVPR*, 2025.
- [35] Alejandro López-Cifuentes, Marcos Escudero-Vinolo, Jesús Bescós, and Álvaro García-Martín. Semantic-aware scene recognition. *Pattern Recognition*, 102:107256, 2020.
- [36] Madeleine Grunde-McLaughlin, Ranjay Krishna, and Maneesh Agrawala. Agqa: A benchmark for compositional spatio-temporal reasoning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11287–11297, 2021.
- [37] Zhiqiu Lin, Deepak Pathak, Baiqi Li, Jiayao Li, Xide Xia, Graham Neubig, Pengchuan Zhang, and Deva Ramanan. Evaluating text-to-visual generation with image-to-text generation. *ArXiv*, abs/2404.01291, 2024.
- [38] Baiqi Li, Zhiqiu Lin, Deepak Pathak, Jiayao Emily Li, Xide Xia, Graham Neubig, Pengchuan Zhang, and Deva Ramanan. Genai-bench: A holistic benchmark for compositional text-to-visual generation. In *Synthetic Data for Computer Vision Workshop@ CVPR 2024*, 2024.
- [39] Jiao Sun, Deqing Fu, Yushi Hu, Su Wang, Royi Rassin, Da-Cheng Juan, Dana Alon, Charles Herrmann, Sjoerd van Steenkiste, Ranjay Krishna, and Cyrus Rashtchian. Dreamsync: Aligning text-to-image generation with image understanding feedback. *ArXiv*, abs/2311.17946, 2023.
- [40] J. Edward Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, and Weizhu Chen. Lora: Low-rank adaptation of large language models. *ArXiv*, abs/2106.09685, 2021.
- [41] Lixue Gong, Xiaoxia Hou, Fanshi Li, Liang Li, Xiaochen Lian, Fei Liu, Liyang Liu, Wei Liu, Wei Lu, Yichun Shi, et al. Seedream 2.0: A native chinese-english bilingual image generation foundation model. *arXiv preprint arXiv:2503.07703*, 2025.
- [42] Dongzhi Jiang, Ziyu Guo, Renrui Zhang, Zhuofan Zong, Hao Li, Le Zhuo, Shilin Yan, Pheng-Ann Heng, and Hongsheng Li. T2i-r1: Reinforcing image generation with collaborative semantic-level and token-level cot. *arXiv preprint arXiv:2505.00703*, 2025.
- [43] Gan Pei, Jiangning Zhang, Menghan Hu, Zhenyu Zhang, Chengjie Wang, Yunsheng Wu, Guangtao Zhai, Jian Yang, Chunhua Shen, and Dacheng Tao. Deepfake generation and detection: A benchmark and survey. *arXiv preprint arXiv:2403.17881*, 2024.
- [44] Tianyi Wang, Xin Liao, Kam Pui Chow, Xiaodong Lin, and Yinglong Wang. Deepfake detection: A comprehensive survey from the reliability perspective. *ACM Computing Surveys*, 2024.
- [45] Achhardeep Kaur, Azadeh Noori Hoshyar, Vidya Saikrishna, Selena Firmin, and Feng Xia. Deepfake video detection: challenges and opportunities. *Artificial Intelligence Review*, 57(6):1–47, 2024.
- [46] Lorenzo Baraldi, Federico Cocchi, Marcella Cornia, Alessandro Nicolosi, and Rita Cucchiara. Contrasting deepfakes diffusion via contrastive learning and global-local similarities. *arXiv preprint arXiv:2407.20337*, 2024.

- [47] Kan Wu, Jinnian Zhang, Houwen Peng, Mengchen Liu, Bin Xiao, Jianlong Fu, and Lu Yuan. Tinyvit: Fast pretraining distillation for small vision transformers. In *European conference on computer vision*, pages 68–85. Springer, 2022.
- [48] Mingjian Zhu, Hanting Chen, Qiangyu Yan, Xudong Huang, Guanyu Lin, Wei Li, Zhijun Tu, Hailin Hu, Jie Hu, and Yunhe Wang. Genimage: A million-scale benchmark for detecting ai-generated image. *Advances in Neural Information Processing Systems*, 36, 2024.
- [49] Tuhin Chakrabarty, Kanishk Singh, Arkadiy Saakyan, and Smaranda Muresan. Learning to follow object-centric image editing instructions faithfully. *ArXiv*, abs/2310.19145, 2023.
- [50] Dustin Podell, Zion English, Kyle Lacey, Andreas Blattmann, Tim Dockhorn, Jonas Müller, Joe Penna, and Robin Rombach. Sdxl: Improving latent diffusion models for high-resolution image synthesis. *arXiv preprint arXiv:2307.01952*, 2023.
- [51] Daiqing Li, Aleks Kamko, Ehsan Akhgari, Ali Sabet, Linmiao Xu, and Suhail Doshi. Playground v2. 5: Three insights towards enhancing aesthetic quality in text-to-image generation. *arXiv preprint arXiv:2402.17245*, 2024.
- [52] Pablo Pernias, Dominic Rampas, Mats L Richter, Christopher J Pal, and Marc Aubreville. Würstchen: An efficient architecture for large-scale text-to-image diffusion models. *arXiv preprint arXiv:2306.00637*, 2023.
- [53] 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 (CVPR)*, pages 10684–10695, June 2022.
- [54] DeepFloyd Lab at StabilityAI. DeepFloyd IF: a novel state-of-the-art open-source text-to-image model with a high degree of photorealism and language understanding. <https://www.deepfloyd.ai/deepfloyd-if>, 2023. Retrieved on 2023-11-08.
- [55] Patrick Esser, Sumith Kulal, Andreas Blattmann, Rahim Entezari, Jonas Müller, Harry Saini, Yam Levi, Dominik Lorenz, Axel Sauer, Frederic Boesel, et al. Scaling rectified flow transformers for high-resolution image synthesis. In *Forty-first International Conference on Machine Learning*, 2024.
- [56] Junsong Chen, Jincheng Yu, Chongjian Ge, Lewei Yao, Enze Xie, Yue Wu, Zhongdao Wang, James Kwok, Ping Luo, Huchuan Lu, et al. Pixart- $\alpha$ : Fast training of diffusion transformer for photorealistic text-to-image synthesis. *arXiv preprint arXiv:2310.00426*, 2023.
- [57] Junsong Chen, Chongjian Ge, Enze Xie, Yue Wu, Lewei Yao, Xiaozhe Ren, Zhongdao Wang, Ping Luo, Huchuan Lu, and Zhenguo Li. Pixart- $\sigma$ : Weak-to-strong training of diffusion transformer for 4k text-to-image generation. *arXiv preprint arXiv:2403.04692*, 2024.
- [58] Black Forest Labs. Flux.1: Advanced text-to-image models, 2024. Accessed: 2024-11-10.
- [59] Jason Baldridge, Jakob Bauer, Mukul Bhutani, Nicole Brichtova, Andrew Bunner, Kelvin Chan, Yichang Chen, Sander Dieleman, Yuqing Du, Zach Eaton-Rosen, et al. Imagen 3. *arXiv preprint arXiv:2408.07009*, 2024.
- [60] Yuwei Guo, Ceyuan Yang, Anyi Rao, Zhengyang Liang, Yaohui Wang, Yu Qiao, Maneesh Agrawala, Dahua Lin, and Bo Dai. Animatediff: Animate your personalized text-to-image diffusion models without specific tuning. *arXiv preprint arXiv:2307.04725*, 2023.
- [61] Fu-Yun Wang, Zhaoyang Huang, Xiaoyu Shi, Weikang Bian, Guanglu Song, Yu Liu, and Hongsheng Li. Animatelcm: Accelerating the animation of personalized diffusion models and adapters with decoupled consistency learning. *arXiv preprint arXiv:2402.00769*, 2024.
- [62] Levon Khachatryan, Andranik Movsisyan, Vahram Tadevosyan, Roberto Henschel, Zhangyang Wang, Shant Navasardyan, and Humphrey Shi. Text2video-zero: Text-to-image diffusion models are zero-shot video generators. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 15954–15964, 2023.

- [63] Jiuniu Wang, Hangjie Yuan, Dayou Chen, Yingya Zhang, Xiang Wang, and Shiwei Zhang. Modelscope text-to-video technical report. *arXiv preprint arXiv:2308.06571*, 2023.
- [64] Tianxing Wu, Chenyang Si, Yuming Jiang, Ziqi Huang, and Ziwei Liu. Freeinit: Bridging initialization gap in video diffusion models. In *European Conference on Computer Vision*, pages 378–394. Springer, 2025.
- [65] Haoxin Chen, Yong Zhang, Xiaodong Cun, Menghan Xia, Xintao Wang, Chao Weng, and Ying Shan. Videocrafter2: Overcoming data limitations for high-quality video diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 7310–7320, 2024.
- [66] Zhuoyi Yang, Jiayan Teng, Wendi Zheng, Ming Ding, Shiyu Huang, Jiazheng Xu, Yuanming Yang, Wenyi Hong, Xiaohan Zhang, Guanyu Feng, et al. Cogvideox: Text-to-video diffusion models with an expert transformer. *arXiv preprint arXiv:2408.06072*, 2024.
- [67] Zangwei Zheng, Xiangyu Peng, Tianji Yang, Chenhui Shen, Shenggui Li, Hongxin Liu, Yukun Zhou, Tianyi Li, and Yang You. Open-sora: Democratizing efficient video production for all, March 2024.
- [68] Ben Poole, Ajay Jain, Jonathan T Barron, and Ben Mildenhall. Dreamfusion: Text-to-3d using 2d diffusion. *arXiv preprint arXiv:2209.14988*, 2022.
- [69] Haochen Wang, Xiaodan Du, Jiahao Li, Raymond A Yeh, and Greg Shakhnarovich. Score jacobian chaining: Lifting pretrained 2d diffusion models for 3d generation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12619–12629, 2023.
- [70] Gal Metzer, Elad Richardson, Or Patashnik, Raja Giryes, and Daniel Cohen-Or. Latent-nerf for shape-guided generation of 3d shapes and textures. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12663–12673, 2023.
- [71] Chen-Hsuan Lin, Jun Gao, Luming Tang, Towaki Takikawa, Xiaohui Zeng, Xun Huang, Karsten Kreis, Sanja Fidler, Ming-Yu Liu, and Tsung-Yi Lin. Magic3d: High-resolution text-to-3d content creation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 300–309, 2023.
- [72] Chengyue Wu, Xiaokang Chen, Zhiyu Wu, Yiyang Ma, Xingchao Liu, Zizheng Pan, Wen Liu, Zhenda Xie, Xingkai Yu, Chong Ruan, et al. Janus: Decoupling visual encoding for unified multimodal understanding and generation. *arXiv preprint arXiv:2410.13848*, 2024.
- [73] Xiaokang Chen, Zhiyu Wu, Xingchao Liu, Zizheng Pan, Wen Liu, Zhenda Xie, Xingkai Yu, and Chong Ruan. Janus-pro: Unified multimodal understanding and generation with data and model scaling. *arXiv preprint arXiv:2501.17811*, 2025.
- [74] Long Lian, Boyi Li, Adam Yala, and Trevor Darrell. Llm-grounded diffusion: Enhancing prompt understanding of text-to-image diffusion models with large language models. *Trans. Mach. Learn. Res.*, 2024, 2023.
- [75] Jialu Li, Jaemin Cho, Yi-Lin Sung, Jaehong Yoon, and Mohit Bansal. Selma: Learning and merging skill-specific text-to-image experts with auto-generated data. *ArXiv*, abs/2403.06952, 2024.
- [76] Rui Zhao, Hangjie Yuan, Yujie Wei, Shiwei Zhang, Yuchao Gu, Lin Hao Ran, Xiang Wang, Zhangjie Wu, Junhao Zhang, Yingya Zhang, and Mike Zheng Shou. Evolvedirector: Approaching advanced text-to-image generation with large vision-language models, 2024.
- [77] Dong Huk Park, Samaneh Azadi, Xihui Liu, Trevor Darrell, and Anna Rohrbach. Benchmark for compositional text-to-image synthesis. In *NeurIPS Datasets and Benchmarks*, 2021.
- [78] Song Wen, Guian Fang, Renrui Zhang, Peng Gao, Hao Dong, and Dimitris Metaxas. Improving compositional text-to-image generation with large vision-language models. *ArXiv*, abs/2310.06311, 2023.

- [79] Xindi Wu, Dingli Yu, Yangsibo Huang, Olga Russakovsky, and Sanjeev Arora. Conceptmix: A compositional image generation benchmark with controllable difficulty. *ArXiv*, abs/2408.14339, 2024.
- [80] Ron Mokady, Amir Hertz, Kfir Aberman, Yael Pritch, and Daniel Cohen-Or. Null-text inversion for editing real images using guided diffusion models. *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 6038–6047, 2022.
- [81] 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*, abs/2208.01618, 2022.
- [82] 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. *2023 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 22500–22510, 2022.
- [83] Spencer Sterling. zeroscope\_v2\_576w, 2023. Accessed: 2024-11-10.
- [84] Y.C. Guo, Y.T. Liu, R. Shao, C. Laforte, V. Voleti, G. Luo, C.H. Chen, Z.X. Zou, C. Wang, Y.P. Cao, and S.H. Zhang. threestudio: A unified framework for 3d content generation. <https://github.com/threestudio-project/threestudio>, 2023.
- [85] Yuval Kirstain, Adam Polyak, Uriel Singer, Shahbuland Matiana, Joe Penna, and Omer Levy. Pick-a-pic: An open dataset of user preferences for text-to-image generation, 2023.
- [86] 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.
- [87] Ziqi Huang, Yinan He, Jiashuo Yu, Fan Zhang, Chenyang Si, Yuming Jiang, Yuanhan Zhang, Tianxing Wu, Qingyang Jin, Nattapol Chanpaisit, et al. Vbench: Comprehensive benchmark suite for video generative models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 21807–21818, 2024.
- [88] Kling AI. Kling ai text-to-video. <https://klingai.com/text-to-video/new>, 2025. Accessed May 23, 2025.
- [89] Team Wan, Ang Wang, Baole Ai, Bin Wen, Chaojie Mao, Chen-Wei Xie, Di Chen, Fei Wu Yu, Haiming Zhao, Jianxiao Yang, Jianyuan Zeng, Jiayu Wang, Jingfeng Zhang, Jingren Zhou, Jinkai Wang, Jixuan Chen, Kai Zhu, Kang Zhao, Keyu Yan, Lianghua Huang, Mengyang Feng, Ningyi Zhang, Pandeng Li, Pingyu Wu, Ruihang Chu, Ruili Feng, Shiwei Zhang, Siyang Sun, Tao Fang, Tianxing Wang, Tianyi Gui, Tingyu Weng, Tong Shen, Wei Lin, Wei Wang, Wei Wang, Wenmeng Zhou, Wenten Wang, Wenting Shen, Wenyuan Yu, Xianzhong Shi, Xiaoming Huang, Xin Xu, Yan Kou, Yangyu Lv, Yifei Li, Yijing Liu, Yiming Wang, Yingya Zhang, Yitong Huang, Yong Li, You Wu, Yu Liu, Yulin Pan, Yun Zheng, Yuntao Hong, Yupeng Shi, Yutong Feng, Zeyinzi Jiang, Zhen Han, Zhi-Fan Wu, and Ziyu Liu. Wan: Open and advanced large-scale video generative models. *arXiv preprint arXiv:2503.20314*, 2025.
- [90] Meshy AI. Meshy ai – text-to-3d, image-to-3d, and text-to-texture 3d model generator. <https://www.meshy.ai>, 2025. Accessed May 23, 2025.
- [91] Jiacheng Liu, Wenya Wang, Dianzhuo Wang, Noah A. Smith, Yejin Choi, and Hannaneh Hajishirzi. Vera: A general-purpose plausibility estimation model for commonsense statements, 2023.
- [92] Xiaoshi Wu, Yiming Hao, Keqiang Sun, Yixiong Chen, Feng Zhu, Rui Zhao, and Hongsheng Li. Human preference score v2: A solid benchmark for evaluating human preferences of text-to-image synthesis. *arXiv preprint arXiv:2306.09341*, 2023.
- [93] Giuseppe Vecchio and Valentin Deschaintre. Matsynth: A modern pbr materials dataset. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 22109–22118, 2024.

- 1380 [94] Sean Bell, Paul Upchurch, Noah Snavely, and Kavita Bala. Material recognition in the wild  
1381 with the materials in context database. In *Proceedings of the IEEE conference on computer  
1382 vision and pattern recognition*, pages 3479–3487, 2015.
- 1383 [95] Jia Xue, Hang Zhang, Kristin Dana, and Ko Nishino. Differential angular imaging for  
1384 material recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern  
1385 Recognition*, pages 764–773, 2017.
- 1386 [96] Mircea Cimpoi, Subhransu Maji, Iasonas Kokkinos, Sammy Mohamed, and Andrea Vedaldi.  
1387 Describing textures in the wild. In *Proceedings of the IEEE conference on computer vision  
1388 and pattern recognition*, pages 3606–3613, 2014.
- 1389 [97] Zhe Xu, Dacheng Tao, Ya Zhang, Junjie Wu, and Ah Chung Tsoi. Architectural style  
1390 classification using multinomial latent logistic regression. In *Computer Vision–ECCV 2014:  
1391 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part I  
1392 13*, pages 600–615. Springer, 2014.
- 1393 [98] Chitwan Saharia, William Chan, Saurabh Saxena, Lala Li, Jay Whang, Emily L Denton,  
1394 Kamyar Ghasemipour, Raphael Gontijo Lopes, Burcu Karagol Ayan, Tim Salimans, et al.  
1395 Photorealistic text-to-image diffusion models with deep language understanding. *Advances in  
1396 neural information processing systems*, 35:36479–36494, 2022.
- 1397 [99] Babak Saleh and Ahmed Elgammal. Large-scale classification of fine-art paintings: Learning  
1398 the right metric on the right feature. *arXiv preprint arXiv:1505.00855*, 2015.
- 1399 [100] Colby Crawford. 1000 cameras dataset. [https://www.kaggle.com/datasets/crawford/  
1400 1000-cameras-dataset](https://www.kaggle.com/datasets/crawford/1000-cameras-dataset), 2018. Accessed: 2024-11-09.
- 1401 [101] Zijie J. Wang, Evan Montoya, David Munechika, Haoyang Yang, Benjamin Hoover, and  
1402 Duen Horng Chau. DiffusionDB: A large-scale prompt gallery dataset for text-to-image  
1403 generative models. *arXiv:2210.14896 [cs]*, 2022.
- 1404 [102] Soravit Changpinyo, Piyush Sharma, Nan Ding, and Radu Soricut. Conceptual 12M: Pushing  
1405 web-scale image-text pre-training to recognize long-tail visual concepts. In *CVPR*, 2021.
- 1406 [103] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image  
1407 recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*,  
1408 pages 770–778, 2016.