DreamDissector: Learning Disentangled Text-to-3D Generation from 2D Diffusion Priors Supplementary File

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1 More Results

1.1 Text Splitting.

The Category Score Distillation Sampling (CSDS) requires splitting the input text prompts into individual objects. We employ GPT-4 for this purpose, a method commonly used and effective for information extraction [5]. We empirically found that GPT-4 has the ability to split very complex text prompts, as shown in Figure 1.

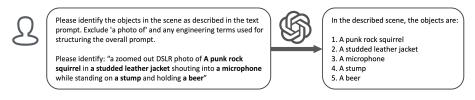


Fig. 1: Text splitting.

1.2 Applications on texture editing

We provide more results on text-guided texture editing, as shown in Figure 2. It can be observed that our method offers greater controllability compared to TEXTure [3].

1.3 Limitations

DreamDissector is likely to fail when objects are in very close contact, such as the body and clothing. We present two examples of this failure in the figure below. The primary reason is the challenge of obtaining clean NeCFs for such complex interactions.

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TEXTure TEXTure Ours Source Source Ours A baby bunny sitting on top of a stack of pancakes -A crocodile playing a drum set dinosaur playing red drum set A white bunny sitting on an oil barrel on the ground A dinos A wine bottle and full wine glass on a chessboard A beer bottle and empty wine glass on a wooden table A confused beagle sitting at a desk A black beagle sitting at a red oak desk A monkey riding a bike A raccoon stealing a pie bike monkey dressed like a doctor riding a golden bike A puppy stealing a burnt pie Fig. 2: Text-guided texture editing. a tiger wearing a tuxedo a chihuahua wearing a tutu

Input Tiger Tiger Tuxedo Tuxedo Input Tuxedo Input Chihuahua Fig. 3: Failure cases.



Tutu

a bunny sitting on a stack of carrots



an iguana holding a balloon





Fig. 4: Qualitative results based on MVDream [4].

1.4 Results on MVDream

We adopt Dreamfusion [2] as the backbone method for generating the initial text-to-3D NeRF for our main results. To verify the versatility of DreamDissector against different backbone methods, we employ MVDream [4], a recently proposed text-to-3D method, as the backbone. Results are shown in Figure 4. It can be observed that DreamDissector successfully dissects MVDream and produces independent textured meshes with improved geometries and textures.

1.5 Results on disentangled text-to-3D generation

We present additional results on disentangled text-to-3D generation, including those featured in the main paper. These results and text prompts are depicted in Figure 5, 6 and 7.

1.6 Comparisons with the baselines

Additional comparisons are shown in Figure 8. It should be noted that negative prompting baseline, being intended to generate independent objects, does not associate with composed objects. Therefore, we regard the entire NeRF as the composed object. We also show the results of a text-guided scene generation method, Set-the-Scene [1], shown in Figure 9. These results illustrate the superior performance of our method.

References

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Fig. 5: Qualitative results based on Dreamfusion [2].

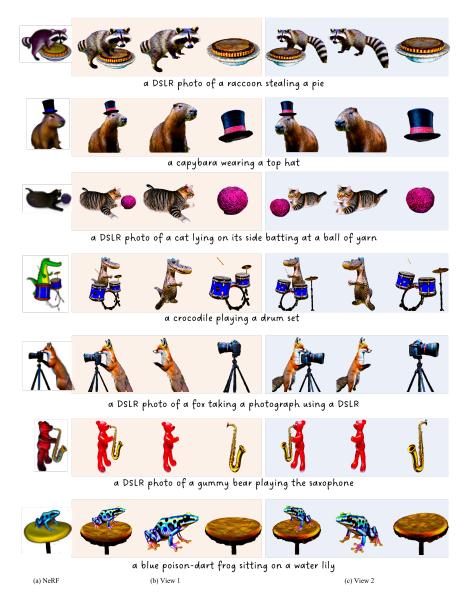


Fig. 6: Qualitative results based on Dreamfusion [2].



Fig. 7: Qualitative results based on Dreamfusion [2].

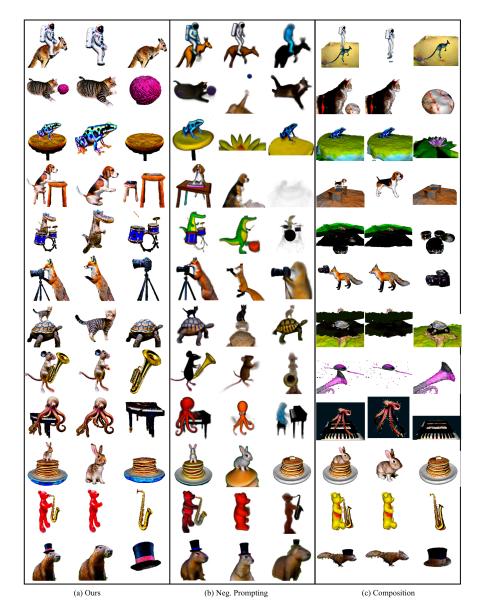


Fig. 8: Comparison with baseline methods.

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A DSLR photo of a baby bunny sitting on a stack of pancakes



A DSLR photo of a mouse playing the tuba



A confused beagle sitting at a desk working on homework



A DSLR photo of a wine bottle and full wine glass on a chessboard



A DSLR photo of an octopus playing the piano



A squirrel riding a motorcycle

Fig. 9: Results on Set-the-Scene. We show the results on set-the-scene. It can be observed that set-the-scene struggles to model the object-interected scenes.