ATT3D: Amortized Text-to-3D Object Synthesis

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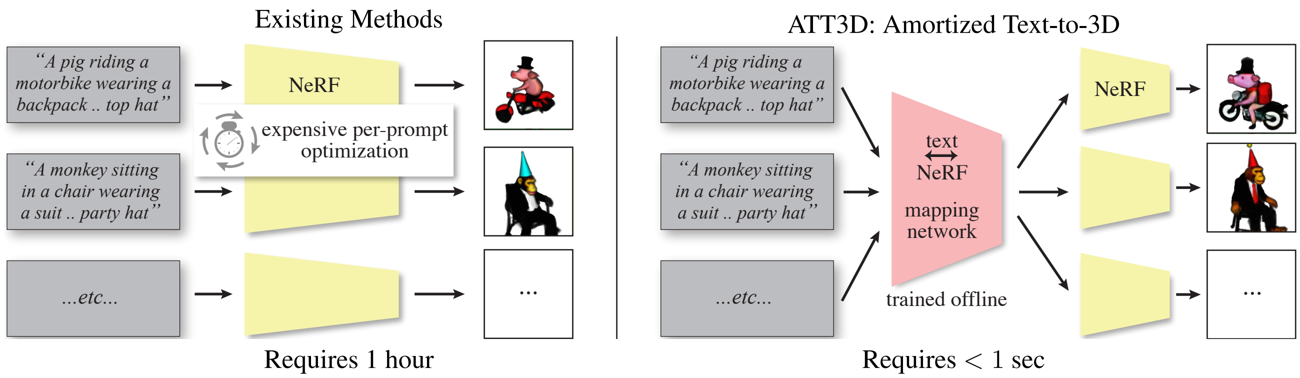

Figure 1: Our method initially trains one network to output 3D objects consistent with various text prompts. After, when we receive an unseen prompt, we produce an accurate object in $<$ 1 second, with 1 GPU. Existing methods re-train the entire network for every prompt, requiring a long delay for the optimization to complete. Further, we can interpolate between prompts for user-guided asset generation (Fig. 3). We include a project webpage with an overview and videos.

Abstract

Text-to-3D modelling has seen exciting progress by combining generative text-to-image models with image-to-3D methods like Neural Radiance Fields. DreamFusion recently achieved high-quality results but requires a lengthy, per-prompt optimization to create 3D objects. To address this, we amortize optimization over text prompts by training on many prompts simultaneously with a unified model, instead of separately. With this, we share computation across a prompt set, training in less time than per-prompt optimization. Our framework – Amortized Text-to-3D (ATT3D) – enables knowledge sharing between prompts to generalize to unseen setups and smooth interpolations between text for novel assets and simple animations.

1. Introduction

3D content creation is important because it allows for more immersive and engaging experiences in industries such as entertainment, education, and marketing. However, 3D design is challenging due to technical complexity of the 3D modeling software, and the artistic skills required to create high-quality models and animations. Text-to-3D (TT3D) generative tools have the potential to democratize 3D content creation by relieving these limitations. To make this technology successful, we desire tools that provide fast responses to users while being inexpensive for the operator.

Recent TT3D methods [1, 2] allow users to generate high-quality 3D models from text-prompts but use a lengthy ($\sim$15 minute to $>$1 hour [1, 2]) per-prompt optimization. Having users wait between each iteration of prompt engineering results in a sporadic and time-consuming design process. Further, generation for a new prompt requires multiple GPUs and uses large text-to-image models [3–5], creating a prohibitive cost for the pipeline operator.

We split the TT3D process into two stages. First, we optimize one model offline to generate 3D objects for many different text prompts simultaneously. This *amortizes optimization* over the prompts, by sharing work between similar instances. The second, user-facing stage uses our amortized model in a simple feed-forward pass to quickly generate an object given text, with no further optimization required.

Our method, Amortized text-to-3D (ATT3D), produces a model which can generate an accurate 3D object in $<$ 1 second, with only 1 consumer-grade GPU. This TT3D pipeline can be deployed more cheaply, with a real-time user experience. Our offline stage trains the ATT3D model significantly faster than optimizing prompts individually while retaining or even surpassing quality, by leveraging compositionality in the parts underlying each 3D object. We also gain a new user-interaction ability to interpolate between prompts for novel asset generation and animations.

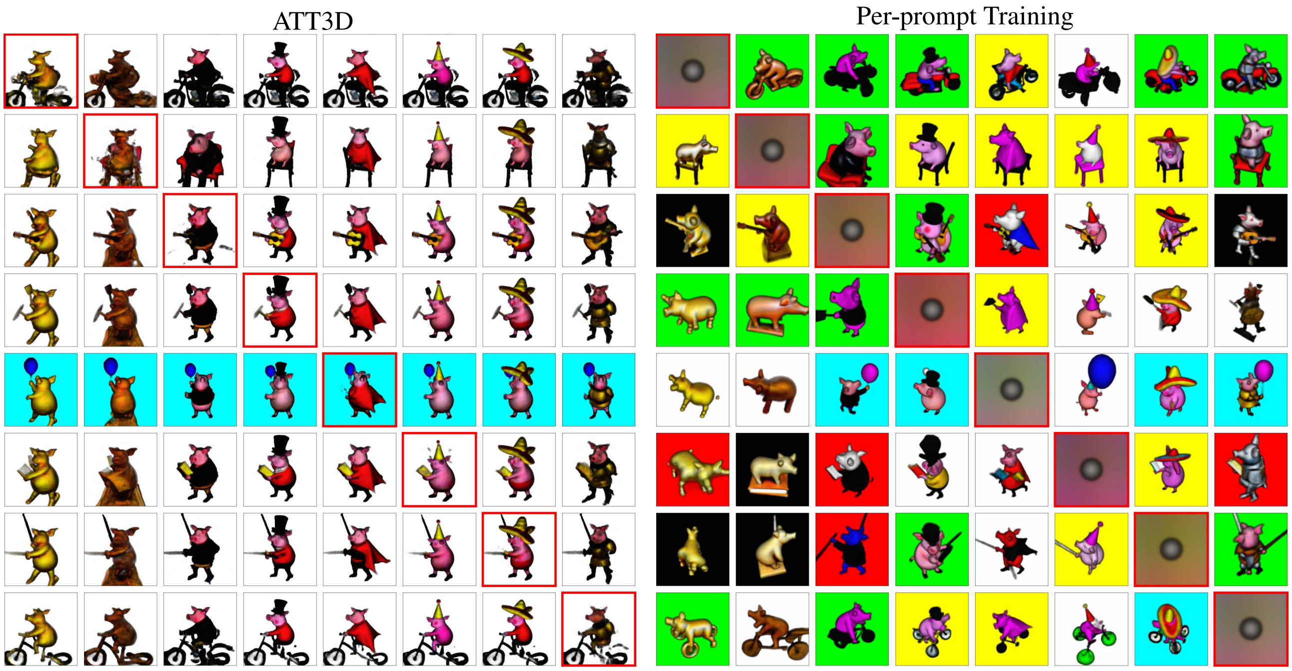

Figure 2: We show results on a compositional prompt set. Each row has a different activity, while each column has a theme, which we combine into the prompt "*a pig* {`activity`} {`theme`}." while we evaluate generalization on a held-out set of unseen testing prompts in red on the diagonal. *Left:* Our method. Interestingly, the amortized objects have a unified orientation. *Right:* The per-prompt training baseline [1], with a random initialization for unseen prompts to align compute budgets. **Takeaway:** Our model performs comparably to per-prompt training on the seen prompts, with a far smaller compute budget (Fig. 6). Importantly, we perform strongly on unseen prompts with no extra training, unlike per-prompt training.

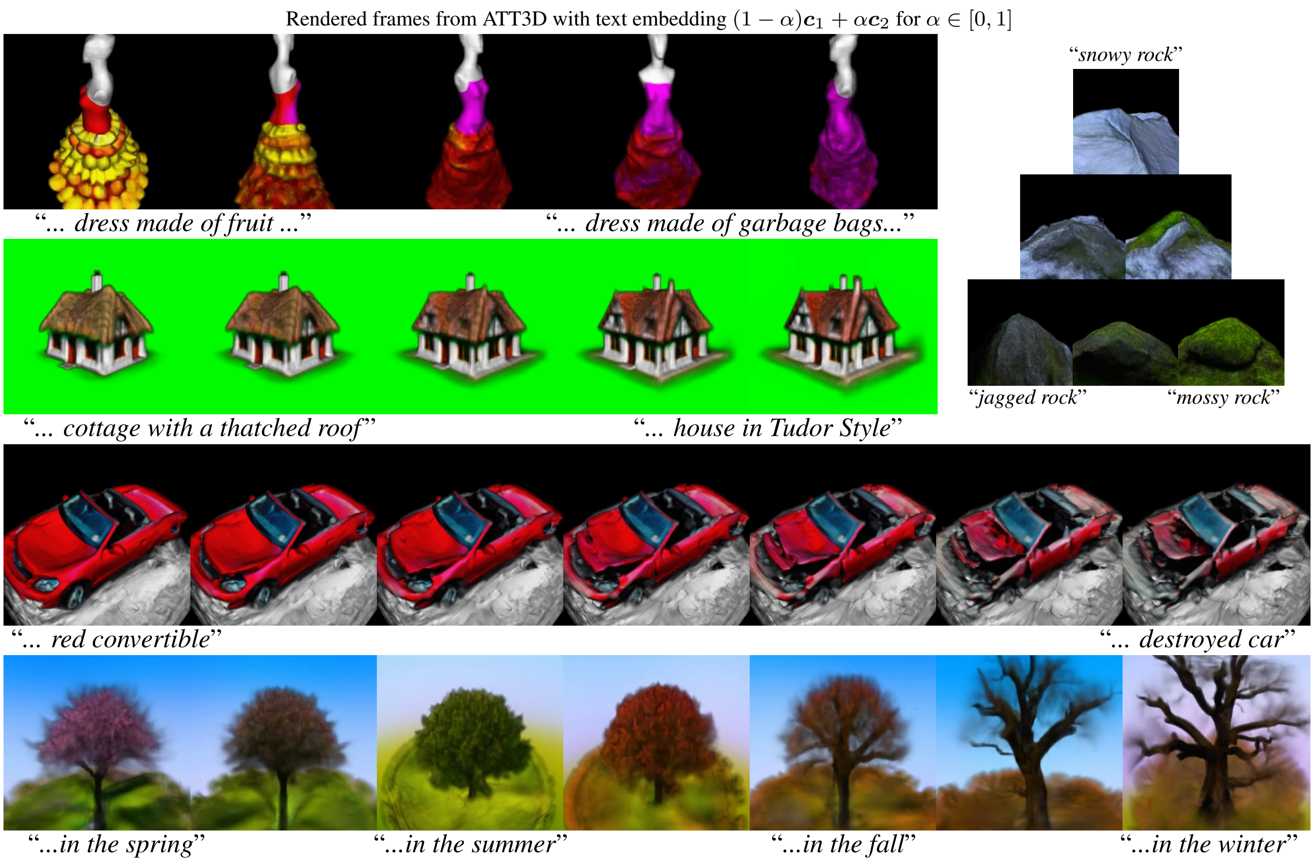

Figure 3: We show renders of our model's output on interpolated text embeddings $(1-\alpha)\boldsymbol{c}_1 + \alpha\boldsymbol{c}_2$. We generate a continuum of landscape, clothing, building, and vehicle assets, and use chains of prompts for animations, like seasonality in a tree.

1.1. Contributions

We present a method to synthesize 3D objects from text prompts immediately. By using amortized optimization we can:

- Generalize to new prompts – Fig. 2.
- Interpolate between prompts – Fig. 3.
- Amortize over settings other than text prompts – Sec. 3.2.2.
- Reduce overall training time – Fig. 6.

2. Background

This section contains concepts and prior work relevant to our method, with notation in App. Table 1.

2.1. NeRFs for Image-to-3D

NeRFs [6] represent 3D scenes via a radiance field parameterized by a neural network. We denote 3D coordinates with $\boldsymbol{x} = [x, y, z] \in \mathcal{X}$ and the radiance values with $\boldsymbol{r} = [\sigma, r, g, b] \in \mathcal{R}$. NeRFs are trained to output radiance fields to render frames similar to multi-view images with camera information. Simple NeRFs map locations $\boldsymbol{x}$ to radiances $\boldsymbol{r}$ via an MLP-parameterized function. Recent NeRFs use spatial grids storing parameters queried per location [7–9], integrating spatial inductive biases. We view this as a *point-encoder* function $\boldsymbol{\gamma}_{\boldsymbol{w}}: \mathcal{X} \to \boldsymbol{\Gamma}$ with parameters $\boldsymbol{w}$ encoding a location $\boldsymbol{x}$ before the final MLP $\boldsymbol{\nu}: \boldsymbol{\Gamma} \to \mathcal{R}$.

$$\boldsymbol{r} = \boldsymbol{\nu}\left(\boldsymbol{\gamma}_{\boldsymbol{w}}\left(\boldsymbol{x}\right)\right) \tag{1}$$

2.2. Text-to-Image Generation

The wide availability of captioned image datasets has enabled the development of powerful text-to-image generative models. We use a DDM with comparable architecture to recent large-scale methods [3–5]. We train for score-matching, where (roughly) input images have noise added to them [10, 11] that the DDM predicts. Critically, these models can be conditioned on text to generate matching images via classifier-free guidance[12]. We use pre-trained T5-XXL [13] and CLIP [14] encoders to generate text embeddings, which the DDM conditions on via cross-attention with latent image features. Crucially, we reuse the text token embeddings – denoted $\boldsymbol{c}$ – for modulating our NeRF.

2.3. Text-to-3D (TT3D) Generation

Prior works rely on per-prompt optimization to generate 3D scenes. Recent TT3D methods [1, 15] use text-to-image generative models to train NeRFs. To do so, they render a view and add noise. The DDM, conditioned on a text prompt, approximates $\boldsymbol{\epsilon}$ with $\hat{\boldsymbol{\epsilon}}$, using the difference $\hat{\boldsymbol{\epsilon}} - \boldsymbol{\epsilon}$ to update NeRF parameters. We outline this method in Alg. 1 and Fig. 4 and refer to DreamFusion Sec. 3 for more details.

2.4. Amortized Optimization

Amortized optimization methods use learning to predict solutions when we repeatedly solve similar instances of the same problem [16]. Current TT3D independently optimizes prompts, whereas, in Sec. 3, we use amortized methods.

A typical amortization strategy is to find a problem context – denoted $\boldsymbol{z}$ – to change our optimization, with some strategies specialized for NeRFs [17]. For example, concatenating the context to the NeRF's MLP: $\boldsymbol{r}(\boldsymbol{x}, \boldsymbol{z}) = \boldsymbol{\nu}(\boldsymbol{\gamma}(\boldsymbol{x}), \boldsymbol{z})$ Or, having a *mapping network* $\boldsymbol{m}$ outputting modulations to the weights or hidden units:

$$\boldsymbol{r}\left(\boldsymbol{x}, \boldsymbol{z}\right) = \boldsymbol{\nu}\left(\boldsymbol{\gamma}_{\boldsymbol{m}(\boldsymbol{z})}\left(\boldsymbol{x}\right)\right) \tag{2}$$

But, designing useful contexts, $\boldsymbol{z}$, can be non-trivial.

3. Our Method: Amortized Text-to-3D

Our method has an initial training stage using amortized optimization, after which we perform cheap inference on new prompts. We first describe the ATT3D architecture and its use during inference, then the training procedure.

3.1. The Amortized Model used at Inference

At inference, our model consists of a *mapping network* $\boldsymbol{m}$, a NeRF $\boldsymbol{\nu}$, and a spatial grid of features $\boldsymbol{\gamma}_{\boldsymbol{w}}$ with parameters $\boldsymbol{w}$ (Fig. 4). The mapping network takes in an (encoded) text prompt $\boldsymbol{c}$ and produces feature grid *modulations*: $\boldsymbol{\gamma}_{\boldsymbol{m}(\boldsymbol{c})}$. Our final NeRF module $\boldsymbol{\nu}$ is a small MLP acting on encoded points $\boldsymbol{\gamma}_{\boldsymbol{m}(\boldsymbol{c})}(\boldsymbol{x})$ – Eq. 1 – representing a 3D object for the text prompt with the modulated feature grid. Full details are in App. Sec. B.1 and summarized here. **Architectural details:** We followed Instant NGP [7] for our NeRF, notably using multi-resolution voxel/hash grids for our point-encoder $\boldsymbol{\gamma}$. We use hypernetwork modulations for implementation and computational simplicity, with alternatives of concatenation and attention considered in App. B.1.3. Hypernetwork approaches output the point-encoder parameters $\boldsymbol{w}$ from a text embedding $\boldsymbol{c}$:

$$\boldsymbol{w} = \text{Hypernetwork}(\boldsymbol{c}) \tag{3}$$

We simply output via a vector $\boldsymbol{v}$ from the text embeddings, which is used to output the parameters via linear maps.

$$\boldsymbol{v} = \text{SiLU}(\text{linear}^{\text{spec.norm}}_{\text{w/ bias}}(\text{flatten}(\boldsymbol{c}))) \tag{4}$$

$$\boldsymbol{w} = \text{reshape}(\text{linear}^{\text{spec.norm}}_{\text{no bias}}(\boldsymbol{v})) \tag{5}$$

This $\boldsymbol{w}$ parameterizes the point-encoder $\boldsymbol{\gamma}_{\boldsymbol{w}}$, which is used to evaluate radiances per-point as per Eq. 1. This simple approach solved our prompt sets, so we used it in all results. Using more sophisticated hypernetworks performed comparably but was slower. However, this may be necessary for scaling to more complicated sets of prompts.

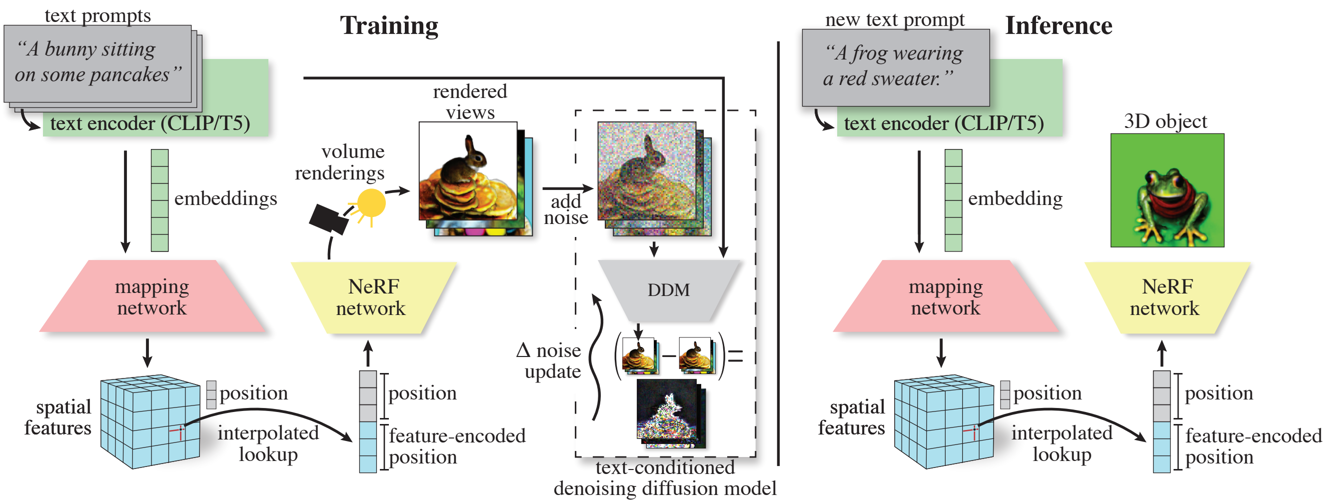

Figure 4: We show a schematic of our text-to-3D pipeline with changes from DreamFusion's pipeline [1] shown in red and pseudocode in Alg. 1. The text encoder (in green) provides its – potentially cached – text embedding $\boldsymbol{c}$ to the text-to-image DDM and now also to the mapping network $\boldsymbol{m}$ (in red). We use a spatial point-encoder $\gamma_{\boldsymbol{m}(\boldsymbol{c})}$ (in blue) for our position $\boldsymbol{x}$, whose parameters are modulations from the mapping network $\boldsymbol{m}(\boldsymbol{c})$. The final NeRF MLP $\boldsymbol{\nu}$ outputs a radiance $\boldsymbol{r}$ given the point encoding: $\boldsymbol{r} = \boldsymbol{\nu}(\gamma_{\boldsymbol{m}(\boldsymbol{c})}(\boldsymbol{x}))$, which we render into views. *Left:* At training time, the rendered views are input to the DDM to provide a training update. The NeRF network $\boldsymbol{\nu}$, mapping network $\boldsymbol{m}$, and (effectively) the spatial point encoding $\gamma_{\boldsymbol{m}(\boldsymbol{c})}$ are optimized. *Right*: At inference time, we use the pipeline up to the NeRF for representing the 3D object.

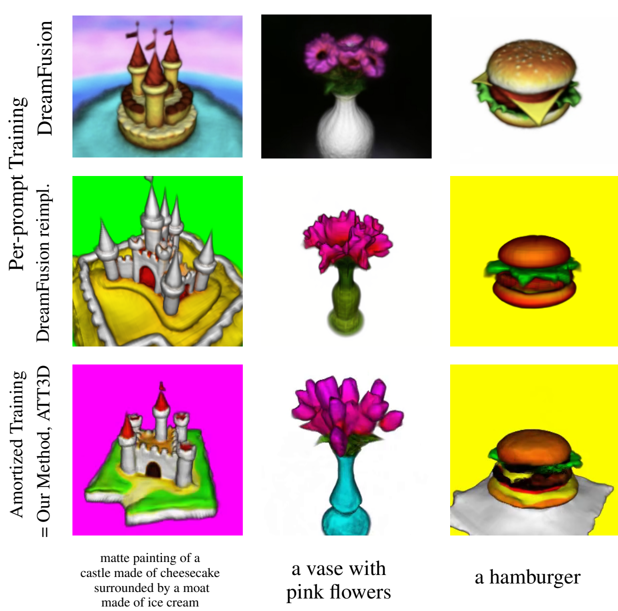

Figure 5: Here we qualitatively assess our method relative to the baseline per-prompt training – i.e., DreamFusion's method. A public DreamFusion implementation is not available. **Takeaway:** Our re-implementation achieves similar quality to the original. Also, our amortized method performs comparably to per-prompt training.

Designing larger prompt sets was challenging because the per-prompt baselines could not effectively handle open-domain text prompts. We partially overcame this limitation by creating compositional prompt sets using prompt components that the underlying model effectively handled.

3.2. Amortized Text-to-3D Training

Alg. 1 overviews our training procedure. In each optimization step, we sample several prompts and produce their – potentially cached – text embeddings $\boldsymbol{z}$, which we use to compute the modulations $\boldsymbol{m}(\boldsymbol{c})$. We also sample camera poses and rendering conditions. These are combined with the NeRF module to render our images. We then use the Score Distillation Sampling loss [1] to update the NeRF.

As in prior work, we augment text prompts depending on camera position – *"..., front/side/rear view"*. We provide the text embeddings (without augmentation) to the mapping network to modulate the NeRF.

3.2.1 Stabilizing Optimization

The NeRF's loss is specified by a denoising diffusion model (DDM) and thus changes during training akin to bilevel setups like GANs [18–20] and actor-critic models [21]. We use techniques from nested optimization to stabilize training motivated by observing similar failure modes. Specifically, we required spectral normalization [19] – crucial for large-scale GANs [20] – to mitigate numerical instability.

Removing optimization momentum helped minimize oscillations from complex dynamics as in nested optimization [22, 23]. Unlike DreamFusion, we did not benefit from Distributed Shampoo [24] and, instead, use Adam [25].

3.2.2 Amortizing Over Other Settings

So far, we described amortizing optimization over many prompts. More generally, we can amortize over other variables like the choice of guidance weight, regularizers, data augmentation, or other aspects of the loss function. We use this to explore techniques for allowing semantically meaningful prompt interpolations, which is a valuable property of generative models like GANs [18] and VAEs [26].

There are various prompt interpolation strategies we can amortize over, like, between text embeddings, guidance weights, or loss functions; see App. Fig. 18 for specifics. To sample an interpolated setup, we sample prompt (embedding) pairs $\boldsymbol{c}_1, \boldsymbol{c}_2$ and an interpolant weight $\alpha \in [0, 1]$. We must give this information to our mapping network - ex., by making it an input $\boldsymbol{m}(\boldsymbol{c}_1, \boldsymbol{c}_2, \alpha)$. Instead, we input interpolated embeddings, allowing an unmodified architecture and incorporating prompt permutation invariance:[1]

$$\boldsymbol{m}\left(\left(1-\alpha\right)\boldsymbol{c}_1 + \alpha\boldsymbol{c}_2\right) \tag{6}$$

In addition to the text prompts distribution, we must choose the interpolant weights α's distribution. For example, we could sample uniform $\alpha \in [0, 1]$, or a binary $\alpha \in \{0, 1\}$ – i.e., training without interpolants – which are both special cases of a Dirichlet distribution. The Dirichlet concentration coefficient is another user choice to change results qualitatively – see App. Fig. 19. We show examples of various loss interpolations in Figs. 3 and 20. The interpolation setup is further details in App. Sec. B.1.14.

3.3. Why We Amortize

Reduce training cost (Fig. 6): We train on text prompts for a fraction of the per-prompt cost.
Generalize to unseen prompts (Fig. 2, 8): We seek strong performance when evaluating our model on unseen prompts during the amortized training without extra optimization.
Prompt interpolations (Fig. 3): Unlike current TT3D, we can interpolate between prompts, allowing: (a) generating a continuum of novel assets, or (b) creating 3D animations.

4. Results and Discussion

Here, we investigate our method's potential benefits. We refer to the baseline as "per-prompt optimization", which follows existing works using separate optimization for each prompt. The specific NeRF rendering and SDS loss implementation are equivalent between the baseline and our method – see Fig. 5. App. Sec. C contains additional experiments, ablations, and visualizations.

[1]By invariance we actually mean $\boldsymbol{m}(\boldsymbol{c}_1,\boldsymbol{c}_2,\alpha) = \boldsymbol{m}(\boldsymbol{c}_2,\boldsymbol{c}_1,1-\alpha)$.

Algorithm 1 ATT3D Pseudocode for each update
Changes from DreamFusion Sec. 3 shown in red

for each loss term in batch **do**
  sample a text and it's embedding $\boldsymbol{c}$
  compute the modulation $\boldsymbol{m}' = \boldsymbol{m}(\boldsymbol{c})$
  sample camera position
  add front/side/back to text, given camera
  sample textureless/shadeless/full render
  perform the render:
    create a ray for each pixel in the frame
    at each ray, sample multiple points $\boldsymbol{x}$
    at each point, compute encoding $\boldsymbol{\gamma}' = \boldsymbol{\gamma}_{\boldsymbol{m}'}(\boldsymbol{x})$
    at each point, compute the radiance $\boldsymbol{\nu}(\boldsymbol{\gamma}')$
    composite radiance into a frame
  add noise to frame
  compute denoised frame with the DDM via $\hat{\boldsymbol{\epsilon}}$
  compute gradient using $\hat{\boldsymbol{\epsilon}} - \boldsymbol{\epsilon}$ as per SDS

4.1. How We Evaluate ATT3D

We first describe the datasets we use, then our metrics for quality and cost.

4.1.1 Our Text Prompt Datasets

DreamFusion (DF): The DF27 dataset consists of the 27 prompts from DreamFusion's main paper, while DF411 has 411 prompts from the project page. We explore memorizing these datasets but find them unsuitable for generalization.
Compositional: To test generalization, we design a compositional prompt set by composing fragments with the template "*a* `{animal}` `{activity}` `{theme}`" and hold out a subset of "unseen" prompts. Our model must generalize to unseen compositions that require nontrivial changes to geometry. Using this template, we created a small pig-prompts and a larger animal-prompts dataset detailed in App. Sec. B.1.12 and shown in Figs. 2 and 8. We hold out 8 out of the 64 pig prompts, as shown in Fig. 2. For the animals, the held-out prompts are sampled homogeneously and we investigate holding out larger fractions of the prompts.

4.1.2 Our Evaluation Metrics

Cost: We measure the computational cost of training per-prompt models versus our amortized approach. Wall-clock time and number of iterations are insufficient because we train with varying compute setups and numbers of GPUs – see App. Sec. B.2. To account for this difference, we measure the number of rendered frames used for training (normalized by the number of prompts). Specifically, this is the number of optimization iterations times batch size divided by the total number of prompts in the dataset.

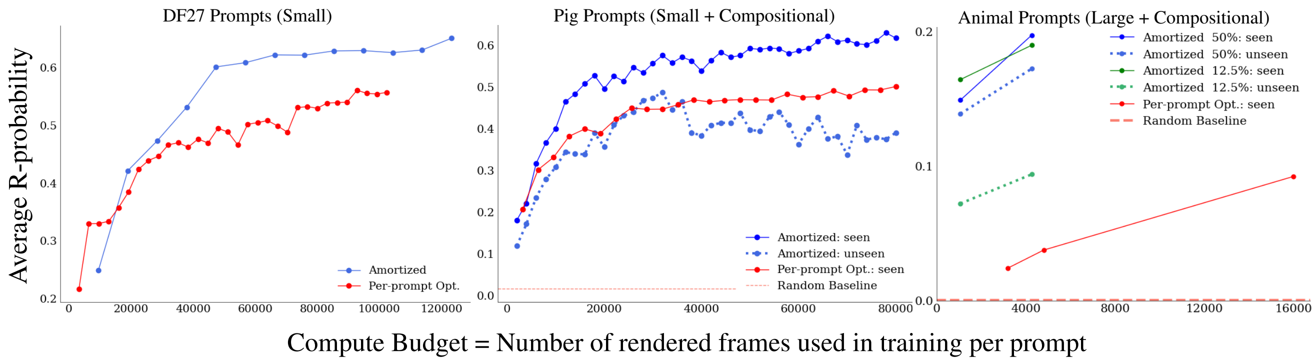

Figure 6: We display the quality against compute budget for a split of **seen** & unseen (dashed) prompts with our method (in blue and green) & existing work's per-prompt optimization baseline (in red). Our method is only trained on the seen split of the prompts. At a given training iteration, the amortized model is evaluated zero-shot on unseen prompts. **Takeaway:** For any compute budget, we achieve a higher quality on both the seen and unseen prompts. Our benefits grow for larger, compositional prompt sets. *Left*: The 27 prompts from DreamFusion (Fig. 11). *Middle*: The 64 compositional pig prompts (Fig. 2). Per-prompt optimization cannot perform zero-shot generation for unseen prompts, so we report the performance of a random initialization baseline. *Right*: The 2400 compositional animal prompts (Fig. 8), with varying prompt proportions used in training. The generalization gap is small when training on 50% of the prompts. Notably, the cheap testing performance is better than the expensive per-prompt method with only 12.5% of the prompts.

Quality: *CLIP R-(prec.)ision* is a text-to-3D correspondence metric introduced in Dream Fields [27], defined as the CLIP model's accuracy at classifying the correct text input of a rendered image from amongst a set of distractor prompts (i.e., the *query set*). *CLIP R-(prob.)ability* is the probability assigned to the correct prompt instead of the binary accuracy, preserving information about confidence, and reducing noise. We found that R- metrics track each other (App. Fig. 12), so we focus on R-prob. We evaluate R-prob. averaged over the input prompt dataset and four distinct rendered views as in DreamFusion [1], using the entire dataset as our query set. The queries in DF27 are highly dissimilar, so we make the metric harder by adding the DF411 prompts to the query set.

4.2. Can We Reduce Training Cost?

Before evaluating generalization, we see if our method can optimize a diverse prompt collection faster than optimizing individually. Fig. 6 gives the R-probability against compute budget for our method & per-prompt optimization, showing we achieved higher quality for any budget. App. Figs. 11 and 14, qualitatively show we accurately memorize all prompts in DreamFusion's main paper and extended prompt set for a reduced cost – perhaps from component reuse as in App. Fig. 15. So, we have a powerful optimization method that quickly memorizes training data.

But does the performance generalize to unseen prompts? Current TT3D methods optimize 1 prompt, so any generalization is a valuable contribution. App. Fig. 16 shows unseen composed and interpolated prompts, with promising results, which we improve in Secs. 4.3 and 4.4 respectively.

4.3. Can We Generalize to Unseen Prompts?

Next, we investigate generalizing to unseen prompts with no extra optimization. We used compositional prompt datasets to evaluate (compositional) generalization in the smaller pig and larger animal prompt datasets. Fig. 6 shows R-probability against compute budget on both seen & unseen prompts for our method & per-prompt optimization showing that we achieved higher quality for any compute budget on both prompt sets. Our generalization is especially evident in the larger prompt set, where we held out a significant fraction of the training prompts. With 50% of prompts withheld, we have a minimal generalization gap. With only 12.5% (300) prompts seen during training, generalization to *unseen prompts* was better than per-prompt optimization on *seen prompts* with only $^1/_4$ the per-prompt compute budget.

To understand the superior performance, we visually compare a subset of pig prompts with the "*holding a blue balloon*" activity in Fig. 7. ATT3D produced more consistent results than per-prompt optimization, potentially explaining our higher R-probability. Visualizations for the pig and animal experiments are in Figs. 2 and 8, respectively. This confirms we can achieve strong generalization performance with a sufficient prompt set. Further, quality can be improved with fine-tuning strategies (App. Fig. 17).

4.4. Can We Make Useful Interpolations?

Next, we investigate our method's ability to create objects as we interpolate between text prompts with no additional test-time optimization. In Fig. 3, we show rendered outputs as we interpolate between different prompts. The output remains realistic with smooth transitions.

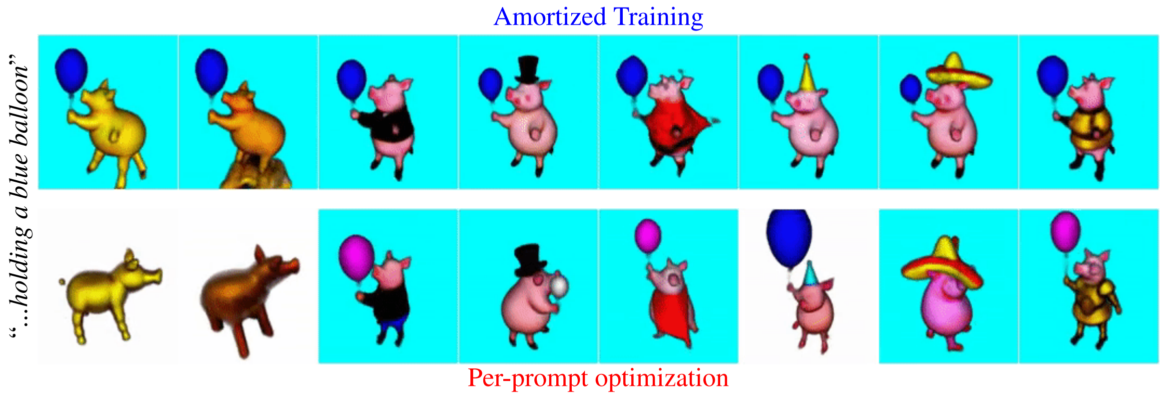

Figure 7: We compare amortized and per-prompt optimization on the prompts of the form "*...holding a blue balloon*." Amortization discovers a canonical orientation and always makes the balloon blue, while per-prompt training may only make the background blue or fail altogether, potentially explaining performance improvements in Fig. 6.

For Fig. 3, top right, we *did not* use loss amortization and generalize to interpolants while only training on the 3 rock prompts. But, some prompts gave suboptimal results without interpolant training (App. Fig. 16) which we improved by interpolant amortization (Sec. 3.2.2). We evaluated several prompt interpolation approaches. App. Fig. 18 compares 3 interpolant amortization types: loss weightings, interpolated embeddings, and guidance weightings, showing various ways to control results. App. Fig. 19 compares different interpolant sampling strategies during training, providing qualitatively different ways to generate assets.

5. Related Work

We cover the various fields our method combines: (a) text-to-image generation, then (b) image-to-3D models, which lead to (c) text-to-3D models, which we augment with (d) amortized optimization.

Text-to-image Generation: (A)TT3D methods [1, 2, 15] use large-scale text-conditional DDMs [3, 4, 28–30], which train using classifier-free guidance to sample images matching text prompts [12]. While these models generate diverse and high-fidelity images for many prompts, they cannot provide view-consistent renderings of a single object and are thus incapable of making 3D assets directly.

Image-to-3D Models: Beyond using 3D assets to train 3D generative models, prior work has also used image datasets. Most of these methods use NeRFs [6, 17, 31–34] as a differentiable renderer optimized to produce image datasets. Differentiable mesh rendering is an alternative [35–38]. Chan et al. [9] are closely related in this category, using a StyleGAN generator modulated with a learned latent code to produce a triplanar grid that is spatially interpolated and fed through a NeRF producing a static image dataset. We also modulate spatially oriented feature grids, without relying on memory-intensive pre-trained generator backbones. These techniques may prove valuable in future work scaling to ultra-large prompt sets.

Text-to-3D Generation: Recent advances include CLIP-forge [39], CLIP-mesh [40], Latent-NeRF [41], Dream Field [27], Score-Jacobian-Chaining [15], & DreamFusion [1]. In CLIP-forge [39], the model is trained for shapes conditioned on CLIP text embeddings from rendered images. During inference, the embedding is provided for the generative model to synthesize new shapes based on the text. CLIP-mesh [40] and Dream Field [27] optimized the underlying 3D representation with the CLIP-based loss. Magic3D adds a finetuning phase with a textured-mesh model [42], allowing high resolutions. Future advances may arise by combining with techniques from unconditional 3D generation [43–45]. Notable open-source contributions are Stable-Dreamfusion [46] and threestudio [47]. Other concurrent works include Zero-1-to-3 [48], Fantasia3D [49], Dream3D [50], DreamAvatar [51], and ProlificDreamer [52]. However, we differ from all of these text-to-3D works, because we amortize over the text prompts.

Amortized Optimization: Amortized optimization [16] is a tool of blossoming importance in learning to optimize [53] and machine learning, with applications to meta-learning [54], hyperparameter optimization [55, 56], and generative modeling [26, 57–59]. Hypernetworks [60] are a popular tool for amortization [55, 56, 61, 62] and have also been used to modulate NeRFs [17, 63, 64], inspiring our strategy. Our method differs from prior works by modulating spatially oriented parameters, and our objective is from a (dynamic) DDM instead of a (static) dataset.

Text-to-3D Animation: Text-to-4D [65] is an approach for directly making 3D animations from text, instead of our interpolation strategy. This is done by generalizing TT3D to use a text-to-video model [28, 66, 67], instead of a text-to-image model. However, unlike us, this requires text-to-video, which can require video data.

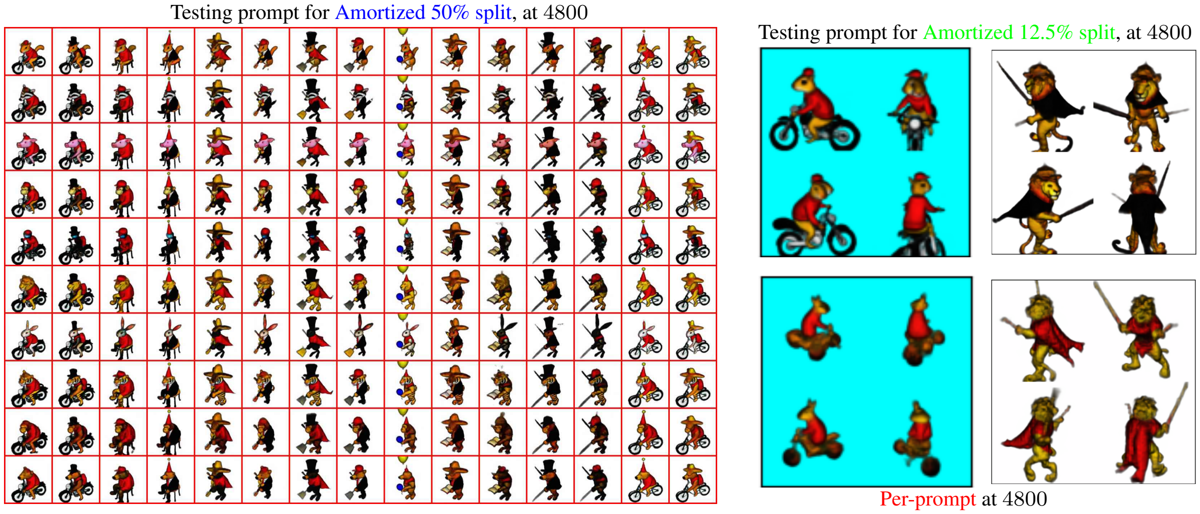

Figure 8: We show quantitative results for the 2400 animal prompts in Fig. 6, where we achieve a higher quality for any compute budget on seen & unseen prompts. Notably, when training on only 50% or 12.5% of the prompts, the unseen prompts – which cost no optimization – perform stronger than the per-prompt method, which must optimize on the data. **Takeaway:** By training a single model on many text prompts we generalize to unseen prompts without extra optimization.

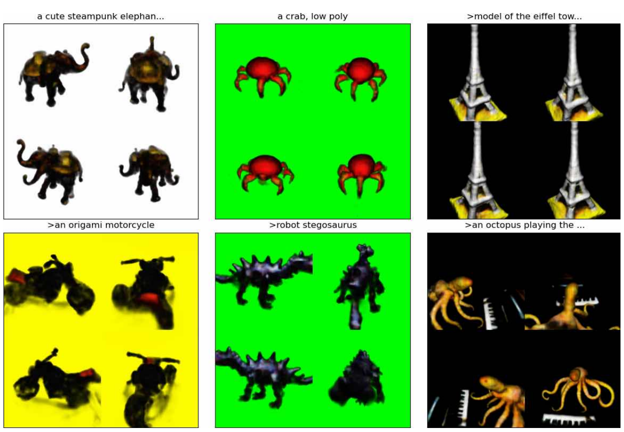

Figure 9: Results for amortized training on DreamFusion's extended set of 411 text prompts, DF411. See Fig. 14 for the full set. **Takeaway:** We scale to diverse prompt sets >10× larger than DF27 (Fig. 11) with minor quality drop.

6. Conclusion

We presented ATT3D, a method for amortized optimization of text-to-3D (TT3D) models. We use a mapping network from text to NERFs, enabling a single model to represent 3D objects of many different prompts. We experimentally validate our method on existing and new compositional prompt sets. We are faster at training than current TT3D methods by sharing the optimization cost across a prompt set. Once trained, our model generalizes by directly outputting objects for prompts unseen during training in a single forward pass. Furthermore, by amortizing over interpolation weights, we quickly generate a continuum of interpolations between prompts, enhancing user control.

Although ATT3D only represents a small step towards general and fast text-to-3D generation, we believe that the ideas presented are a promising avenue toward this future.

Limitations: Our method builds on the existing text-to-3D optimization paradigm, so we share several limitations with these works: More powerful text-to-image DDMs may be required for higher quality and robustness in results. The objective has high variance, and the system can be sensitive to prompt engineering. We also suffer from a lack of diversity, as in prior work. We found that similar prompts can collapse to the same scene when amortizing. Finally, larger object-centric prompt sets are required to further test the scaling of amortized training.

Ethics Statement: Text-to-image models carry ethical concerns for synthesizing images, which text-to-3D models like this share. For example, we may inherit any biases in our underlying text-to-image model. These models could displace creative jobs or enable the growth and accessibility of 3D asset generation. Alternatively, 3D synthesis models could be used to generate misinformation by bad actors.

Reproducibility Statement: Our instant-NGP NeRF backbone is publicly available through the "instant-ngp" repository [7]. While our diffusion model is not publicly available (as in DreamFusion [1]), other available models may be used to produce similar results. To aid reproducibility, we include a method schematic in Fig. 4 and pseudocode in Alg. 1. Our evaluation setup is in Sec. 4.1 along with hyperparameters and other details in App. Sec. B.

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